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Methodological review of multicriteria optimization techniques: Applications
in water resources

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EXECUTIVE SUMMARY

Multi-criteria decision analysis (MCDA) is an umbrella approach that has been applied to a wide range of natural resource management situations. This report has two purposes.

First, it aims to provide an overview of advanced multicriteria approaches, methods and tools. The review seeks to layout the nature of the models, their inherent strengths and limitations. Analysis of their applicability in supporting real-life decision-making processes is provided with relation to requirements imposed by organizationally decentralized and economically specific spatial and temporal frameworks. Models are categorized based on different classification schemes and are reviewed by describing their general characteristics, approaches, and fundamental properties. A necessity of careful structuring of decision problems is discussed regarding planning, staging and control aspects within broader agricultural context, and in water management in particular. A special emphasis is given to the importance of manipulating decision elements by means of hierarching and clustering. The review goes beyond traditional MCDA techniques; it describes new modelling approaches.

The second purpose is to describe new MCDA paradigms aimed at addressing the inherent complexity of managing water ecosystems, particularly with respect to multiple criteria integrated with biophysical models, multistakeholders, and lack of information. Comments about, and critical analysis of, the limitations of traditional models are made to point out the need for, and propose a call to, a new way of thinking about MCDA as they are applied to water and natural resources management planning. These new perspectives do not undermine the value of traditional methods; rather they point to a shift in emphasis from methods for problem solving to methods for problem structuring.

Literature review show successfully integrations of watershed management optimization models to efficiently screen a broad range of technical, economic, and policy management options within a watershed system framework and select the optimal combination of management strategies and associated water allocations for designing a sustainable watershed management plan at least cost. Papers show applications in watershed management model that integrates both natural and human elements of a watershed system including the management of ground and surface water sources, water treatment and distribution systems, human demands, wastewater treatment and collection systems, water reuse facilities, nonpotable water distribution infrastructure, aquifer storage and recharge facilities, storm water, and land use

INTRODUCTION

By the end of 2000, the European Commission published the Water Framework Directive (WFD) 2000/60/CE, establishing a framework for common action in the field of water policy that may be considered as the “most significant piece of European water legislation for over twenty years” [Foster et al., 2000]. This new legislation, through its 26 articles, provides the basis to achieve the sustainable management of water resources following an integrated approach.

After this WFD, many difficulties have arisen for policy-makers, when they have to deal with decisions related to the environmental field and, in particular, with water management. Integrated Water Resources Planning and Management is considered a very complex issue, since it is usually solved by multisectorial-interdisciplinary hierarchical decomposition approaches. In general, integrated management indicates the consideration of water, socio-economic and environmental issues.

However, and to complicate the process even further, it is also necessary to consider, as in general environmental planning, that there is a large number of decision-makers involved in the process with conflicting preferences and judgement values [Lahdelma et al. 2000].

In this regard, decision problems concerning environmental and natural resources management are usually complex or even hyper-complex problems [Brans, 2002]. A deep analysis and decision making process requires a high background on environmental, economic and social disciplines. At this point, sometimes it is not easy to develop policies with the agreement of all the policy units involved in the water resources management.

The existing links between water policy and other related fields entails that decisions in water resources management affect, and are affected by other policy areas. So we cannot consider water policy as an isolated task, nor can the development of policies in other areas be accomplished without referencing them to water policy. Areas like environment, energy, industry, agriculture, tourism have an important role on the management of water resources and water policy.

By using multicriteria methods we do not aim at obtaining the right answer when we have to decide between different sets of policy options, nor at providing an objective analysis which will relieve decision makers from their responsibility of making difficult judgements. Rather, we aim at making the subjective judgements explicit, and the process through which they are taken into account transparent, a very important issue when a large number of actors are involved in the decision process [Belton et al., 2002].

Many applications of multicriteria analysis (MCA) conclude that their main value does not lie in providing the ‘answer’, but in endowing such process with an improved transparency; setting a better structuring of the problems; and facilitating decision maker learning [Ananda and Herath, 2003]; [Prato, 1999]; [Mills et al., 1996]. Even if decision makers disagree with MCA’s output, it can still provide a valuable input to the decision procedure [RAC, 1992]. The notion of MCA as a ‘glass box’, rather than a ‘black box’, suggests that those using MCA techniques can understand in a better way the implicit trade-offs and appreciate the consequences of alternative preference-positions. Arguments for adopting formalized MCA over otherwise decision makers’ unaided and informal selection procedures often rest upon its capacity to improve the decision procedure by making choices analytically robust, accountable and auditable [Dunning et al., 2000; Schultz, 2001].

DELIVERABLE OBJECTIVES

The objective of this report is to make a review of existing literature on Multi-Criteria Optimization (MCO) tools, linked to biophysical models used in the field of water management. This task is subdivided into 2 sub-tasks:

- Review of MCO: Review existing methodology of multi criteria optimization techniques, with a focus on methodologies, their strengths and weaknesses in view of their application to the present case.
- Review of biophysical models linked to MCO: Review of the actual use of MCO and biophysical models in the field of water resources management

DEFINITIONS, ACRONYMS, ABBREVIATIONS

ACO	Ant Colony Optimization
AHP	Analytical Hierarchy Process
BCA	Benefit Cost Analysis
CP	Compromise Programming
DEA	Data Envelopment Analysis
DM	Decision Maker
DSS	Decision Support Systems
EA	Evolutionary Algorithm
ES	Expert Systems
GA	Genetic Algorithms
GIS	Geographic Information Systems
GP	Goal Programming
IWI	Index of Watershed Indicators
IWRM	Integrated Water Resource Management
KBS	Knowledge Based Systems
MADM	Multi-attribute Decision Making
MAUT	Multi-Attribute Utility Theory
MCA	Multi-Criteria Analysis
MCDA	Multi-Criteria Decision Analyses
MCDM	Multicriteria Decision Making
MCO	Multi-Criteria Optimization
MODE	Multi-objective Differential Evolution
MODS	Multiple Objective Decision Support
MOILP	Multiple Objective Integer Linear Programming
MOLP	Multiple Objective Linear Programming)
MOMP	Multi-Objective Mathematical Programming
MOO	Multi-Objective Optimization
MOOP	Multi-Objective Optimization Problem
NMOO	Nonlinear Multiple Objective Optimization

SA	Simulated Annealing
SAW	Simple Additive Weighting
SMART	Simple Multiattribute Rating Technique
SPW	Simple Product Weighting
SSE	Stochastic Search Engines
SWAT	Soil and Water Assessment Tool
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TS	Tabu Search
WFD	Water Framework Directive

STRUCTURE OF THE DOCUMENT

The third section is a general introduction to optimization problems. Next section describes the differences between univariate and multivariate optimization problems, in order to undertake a detailed review of the classifications of multi-criteria decision methods, with special emphasis on stochastic optimization techniques. Section five presents the applications which are ‘state of the art’, and that integrate multi-criteria optimization and biophysical models, especially those devoted to link biophysical models used in the field of water management. Finally, the bibliography and an annex with alternative classifications of MCDA methods are presented.

One of the most fundamental principles in our world is the search for an optimal state. It begins in the microcosm where atoms in physics try to form bonds¹ in order to minimize the energy of their electrons [Pauling 1960]. When molecules form solid bodies during the process of freezing, they try to assume energy-optimal crystal structures. These processes, of course, are not driven by any higher intention but purely result from the laws of physics.

The same goes for the biological principle of survival of the fittest [Spencer, 1867] which, together with the biological evolution [Darwin, 1859], leads to better adaptation of the species to their environment. Here, a local optimum is a well-adapted species that dominates all other animals in its surroundings. Homo sapiens have reached this level, sharing it with ants, bacteria, flies, cockroaches, and all sorts of other creepy creatures.

As long as humankind exists, we strive for perfection in many areas. We want to reach a maximum degree of happiness with the least amount of effort. In our economy, profit and sales must be maximized and costs should be as low as possible. Therefore, optimization is one of the oldest of sciences which even extends into daily life [Neumaier, 2006].

The goal of global optimization is to find the best possible elements x^* from a set X according to a set of criteria $F = \{f_1, f_2, \dots, f_n\}$. These criteria are expressed as mathematical functions, the so-called objective functions. A mathematical optimization model consists mainly three basic sets of elements:

- **Objective function:** the objective function defines the measure of effectiveness of the system as a mathematical function of decision variables.
- **Variables and parameters of decision:** the decision variables are the unknowns, or decisions, to be determined by solving the model. The parameters are known values which relate the decision variables with constraints and objective function. The model parameters can be deterministic or probabilistic.
- **Constraints:** To take account of technological, economic and other system, the model should include constraints, implicit or explicit, that restrict decision variables to a range of feasible values

CLASSIFICATION OF OPTIMIZATION ALGORITHMS

In this chapter, we will provide a rough classification of the different optimization techniques which are a small fraction of the wide variety of global optimization techniques [Panos et al, 2000]

1.1.1 Classification According to Method of Operation

Figure 3.1 sketches a rough taxonomy of global optimization methods. Generally, optimization algorithms can be divided in two basic classes: deterministic and probabilistic algorithms. Deterministic algorithms are most often used if a clear relation between the characteristics of the possible solutions and their utility for a given problem exists. Then, the search space can efficiently be explored using for example a divide and conquer scheme. If the relation between a solution candidate and its “fitness” are not so obvious or too complicated, or the dimensionality of the search space is very high, it becomes harder to solve a problem deterministically. Trying it would possible result in exhaustive enumeration of the search space, which is not feasible even for relatively small problems.

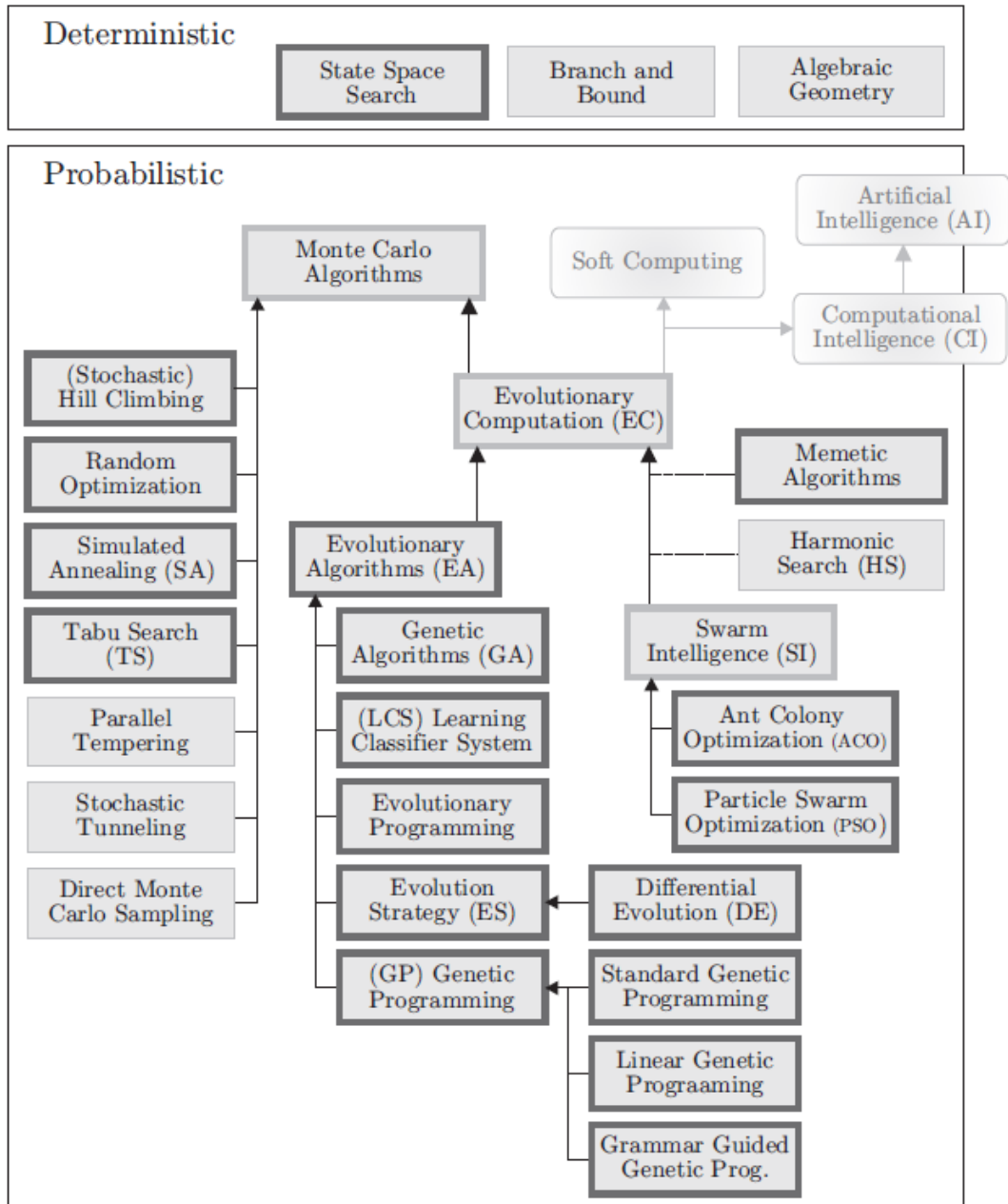


Figure 3.1: The taxonomy of global optimization algorithms [Weise, 2009]

Then, probabilistic algorithms come into play. Especially relevant in this context are Monte Carlo based approaches [Robert et al., 2006]. They trade in guaranteed correctness of the solution for a shorter runtime. This does not mean that the results obtained using them are incorrect, they may just not be the global optima. On the other hand, a solution a little bit inferior to the best possible one is better than one which needs 10^{100} years to be found.

Heuristics used in global optimization are functions that help decide which one of a set of possible solutions is to be examined next. On one hand, deterministic algorithms usually employ heuristics in order to define the processing order of the solution candidates. Probabilistic methods, on the other hand, may only consider those elements of the search space in further computations that have been selected by the heuristic.

A **heuristic** [Michalewicz & Fobel 2004][Rayward-Smith et al, 1996] is a part of an optimization algorithm that uses the information currently gathered by the algorithm to help to decide which solution candidate should be tested next or how the next individual can be produced. Heuristics are usually problem class dependent.

A **metaheuristic** is a heuristic method for solving a very general class of problems. It combines objective functions or heuristics in an abstract and hopefully efficient way, usually without utilizing deeper insight into their structure.

This combination is often performed stochastically by utilizing statistics obtained from samples from the search space or based on a model of some natural phenomenon or physical process. Simulated annealing, for example, decides which solution candidate to be evaluated next according to the Boltzmann probability factor of atom

configurations of solidifying metal melts. Evolutionary algorithms copy the behaviour of natural evolution and treat solution candidates as individuals that compete in a virtual environment.

An important class of probabilistic, Monte Carlo metaheuristics is Evolutionary Computation [Heitkötter & Beasley, 1998]. It encompasses all algorithms that are based on a set of multiple solution candidates, called population, which are iteratively refined. This field of optimization is also a class of Soft Computing [Zadeh, 1994] as well as a part of the artificial intelligence [Buchanan, 2005] area. Some of its most important members are evolutionary algorithms and Swarm Intelligence. Besides these nature-inspired and evolutionary approaches, there exist also methods that copy physical processes like the before-mentioned Simulated Annealing, Parallel Tempering, and Raindrop Method, as well as techniques without direct real-world role model like Tabu Search [Glover & Laguna, 1998] and Random Optimization.

1.1.2 Classification According to Properties

The taxonomy just introduced classifies the optimization methods according to their algorithmic structure and underlying principles, in other words, from the viewpoint of theory. A software engineer or a user who wants to solve a problem with such an approach is however more interested in its “interfacing features” such as speed and precision.

Speed and precision are conflicting objectives, at least in terms of probabilistic algorithms. A general rule of thumb is that you can gain improvements in accuracy of optimization only by investing more time. Scientists in the area of global optimization try to push this Pareto frontier [Pareto, 1906] further by inventing new approaches and enhancing or tweaking existing ones.

Optimization Speed. When it comes to time constraints and hence, the required speed of the optimization algorithm, we can distinguish two main types of optimization use cases.

Online optimization problems are tasks that need to be solved quickly in a time span between ten milliseconds to a few minutes. In order to find a solution in this short time, optimality is normally traded in for speed gains. Examples for online optimization are robot localization, load balancing, services composition for business processes, or updating a factory’s machine job schedule after new orders came in. From the examples, it becomes clear that online optimization tasks are often carried out repetitively new orders will, for instance, continuously arrive in a production facility and need to be scheduled to machines in a way that minimizes the waiting time of all jobs.

In **offline optimization** problems, time is not so important and a user is willing to wait maybe even days if she can get an optimal or close to-optimal result. Such problems regard for example design optimization, data mining, or creating long-term schedules for transportation crews. These optimization processes will usually be carried out only once in a long time. Before doing anything else, one must be sure about to which of these two classes the problem to be solved belongs.

SINGLE OBJECTIVE FUNCTIONS

Optimization algorithms also can be divided in such which try to find the best values of single objective functions f and such that optimize sets F of target functions. This distinction between single-objective optimization and multi-objective optimization is discussed in depth in Section 4.1.

We have already said that global optimization is about finding the best possible solutions for given problems. Thus, it cannot be a bad idea to start out by discussing what it is that makes a solution optimal.

In the case of optimizing a single criterion f , an optimum is either its maximum or minimum, depending on what we are looking for. If we own a manufacturing plant and have to assign incoming orders to machines, we will do this in a way that minimizes the time needed to complete them. On the other hand, we will arrange the purchase of raw material, the employment of staff, and the placing of commercials in a way that maximizes our profit. In global optimization, it is a convention that optimization problems are most often defined as minimizations and if a criterion f is subject to maximization, we simply minimize its negation ($-f$).

Figure 3.2 illustrates such a function f defined over a two-dimensional space $X = (X_1, X_2)$. As outlined in this graphic, we distinguish between local and global optima. A global optimum is an optimum of the whole domain X while a local optimum is an optimum of only a subset of X .

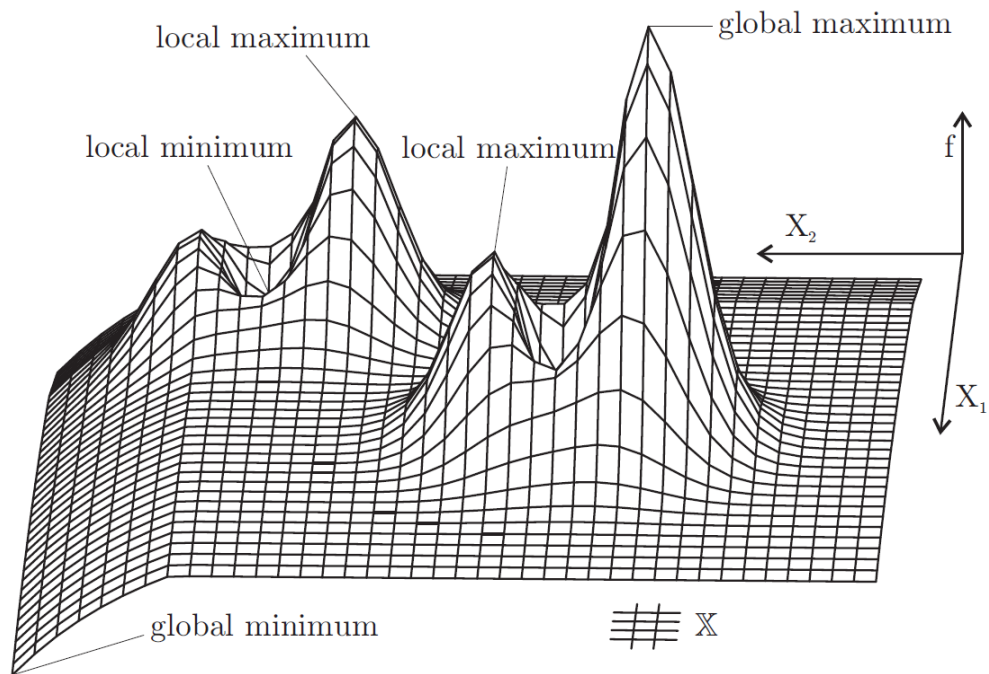


Figure 3.2: Global and local optima of a two-dimensional function. [Weise, 2009]

There is no simple answer to which optimization method is the best for any given problem. It is all a matter of opinion; very much depending on the nature of the problem and the availability of different optimization software that fits the problem statement.

In most comparison studies different methods come out on top depending on the problem and how well the different methods have been tuned to fit that particular problem. Comparative studies of different types of non-derivative methods could be found in for instance [Borup and Parkinson, 1992] [Hajela, 1999] [Mongeau et al., 1998]. An interesting question that one should keep in mind when comparing different methods are the time spent on optimizing the different methods before they are compared. If a method is five percent faster than another one, but takes three times as long to implement and parameterize, it might not be worth the effort.

MULTI OBJECTIVE FUNCTIONS

In many practical problems, several optimization criteria need to be satisfied simultaneously. Moreover, it is often not advisable to combine them into a single objective. While it may sometimes happen that a single solution optimizes all of the criteria, the more likely scenario is when one solution is optimal with respect to a single criterion while other solutions are best with respect to the other criteria. The increase of the “goodness” of the solution with respect to one objective will produce a decrease of its “goodness” with respect to the others. While there are no problems in understanding the notion of optimality in single objective problems, multiobjective optimization requires the concept of Pareto-optimality.

Real environmental and engineering problems are usually characterized by the presence of many conflicting objectives that the design has to fulfil. Therefore, it is natural to look at the engineering or environmental problem as a multiobjective optimization problem (MOOP).

Multiobjective Optimisation (MOO) has its roots in the principles of economics and mathematics. It was initially restricted to economics field but has, in the recent decades, found its way to engineering where different objectives, conflicting or not, are all considered to be of importance. MOO is a generalization of Single Objective Optimization with the main distinction being that the former yields different values for the same objective function for the optimal solutions while the same objective function value is obtained for different optimal solutions in the latter.

If a scenario involves an arbitrary optimization problem with M objectives, all of which to be maximized and equally important, a general multi-objective problem can be formulated as follows:

$$\begin{aligned} & \text{maximize} \quad f_m(x), \quad m = 1, 2, \dots, M \\ & \text{subject to:} \quad g_j(x) \geq 0, \quad j = 1, 2, \dots, J \\ & \quad \quad \quad h_k(x) = 0, \quad k = 1, 2, \dots, K \\ & \quad \quad \quad x_i^{(L)} \leq x_i \leq x_i^{(U)} \quad i = 1, 2, \dots, n \end{aligned}$$

where x is a vector of n decision variables: $x = (x_1, x_2, \dots, x_n)^T$. In this case, a Pareto optimal objective vector $f^* = (f_1^*, f_2^*, \dots, f_M^*)$ is such that it does not exist any feasible solution x' , and corresponding objective vector $f' = (f_1', f_2', \dots, f_M') = (f_1(x'), f_2(x'), \dots, f_M(x'))$ such that $f_m^* \leq f_m'$ for each $m = 1, 2, \dots, M$ and $f_j^* < f_j'$ for at least one $1 \leq j \leq M$.

Many terms and fundamental ideas stem from these fields. The reader is referred to [Stadler and Dauer 1992], and [Stadler 1988] for extensive discussions of these topics and for the history of multi-objective optimization.

The main elements of a decision problem include the design of promising, feasible alternatives and the subsequent selection of a solution, alternative, from a set of alternatives thus generated or identified. This decision process is based on:

1. A set of **Alternatives**, which can be discrete and pre-existing, or generated on demand;
2. A set of **Criteria** describing each of the alternatives; criteria can be qualitative or quantitative, cardinal, ordinal or nominal.
3. **Constraints** describing acceptable lower or upper bounds on any one of the criteria; only a solution that meets all constraints is deemed a feasible alternative and subsequently considered.
4. **Objectives** or objective function(s), expressed in terms of the criteria that should be minimized or maximized by the selection.
5. A **preference structure** that defines the relative importance of different criteria in contributing to the objective function, and the different importance of different objectives in an overall evaluation

BASIC CONCEPTS AND DEFINITIONS

1.1.3 Preferences

Preferences refer to a decision-maker's opinions concerning points in the criterion space. With methods that involve a posterior articulation of preferences, the decision-maker imposes preferences directly on a set of potential solution points. Then, theoretically the final solution reflects the decision-maker's preferences accurately. With a priori articulation of preferences, one must quantify opinions before actually viewing points in the criterion space. In this sense, the term preference often is used in relation to the relative importance of different objective functions. Nonetheless, this articulation of preferences is fundamentally based on opinions concerning anticipated points in the criterion space.

A preference function is an abstract function, of points in the criterion space, in the mind of the decision-maker, which perfectly incorporates his/her preferences.

1.1.4 Utility Function

In the context of economics, utility, which is modelled with a utility function, represents an individual's or group's degree of contentment [Mansfield 1985]. This is slightly different from the usual meaning of usefulness or worth. Instead, in this case, utility emphasizes a decision-maker's satisfaction. In terms of multiobjective optimization, an individual utility function is defined for each objective and represents the relative importance of the objective. The utility function U is an amalgamation of the individual utility functions and is a mathematical expression that attempts to model the decision-maker's preferences. It is used to approximate the preference function, which typically cannot be expressed in mathematical form.

1.1.5 Global Criterion

A global criterion is a scalar function that mathematically combines multiple objective functions; it does not necessarily involve utility or preference.

1.1.6 Game Theory

Stadler [Stadler,1988] writes that "the mathematical and economic approaches [to multi-objective problems] were eventually united with the inception of game theory." According to the traditional game theory interpretation, a game is any situation of conflict or cooperation between at least two players with multiple possible strategies or moves. Game theory represents multi-objective optimization with multiple decision-makers, each controlling certain design variables [Vincent 1983]. If all players cooperate, the result is the same as a single player acting as a decision-maker for a multi-objective optimization problem.

One of the predominant classifications of multiobjective approaches is that of scalarization methods and vector optimization methods. Given a vector of objective functions, it is possible simply to combine the components of this vector to form a single scalar objective function, hence the term scalarization. Although few authors make the distinction, the term vector optimization loosely implies independent treatment of each objective function. Both approaches are discussed in this study.

1.1.7 Pareto Optimality

Pareto efficiency, or Pareto optimality, is a concept in economics with applications in engineering and social sciences. The term is named after Vilfredo Pareto [Pareto 1906], an Italian economist who used the concept in his studies of economic efficiency and income distribution.

In many practical problems, several optimization criteria need to be satisfied simultaneously. Moreover, it is often not advisable to combine them into a single objective. While it may sometimes happen that a single solution optimizes all of the criteria, the more likely scenario is when one solution is optimal with respect to a single criterion while other solutions are best with respect to the other criteria. The increase of the "goodness" of the solution with respect to one objective will produce a decrease of its "goodness" with respect to the others. While there are no problems in understanding the notion of optimality in single objective problems, multiobjective optimization requires the concept of Pareto-optimality.

The solution is said to be Pareto-optimal (belongs to the Pareto-optimal front, or set of solutions) if, with its change not one objective function can be improved without degrading all of the others. All of the solutions that make up a Pareto-optimal front are said to be nondominated, by other solutions. Concepts of the Pareto optimal front, non-dominated and dominated solutions are further explained in figure 4.1. The axes on figure 4.1 ($F_1 = 1/\text{irrigation}$ and $F_2 = \text{yield}$) are two objective functions. Possible solutions for maximization are presented in the F_1 - F_2 plane. Solutions marked with red circles are called nondominated and they make up the Pareto-optimal front. Those marked with blue circles are the dominated. non- Pareto optimal, solutions.

A feasible point is considered to be a solution to a multi-objective optimization problem, and is called Pareto optimal, when there exist no other feasible point that improves one of the objectives without worsening at least one of the other objectives. The set of these mathematically equivalent point is often referred to as the Pareto set or Pareto front (red points in the next figure)

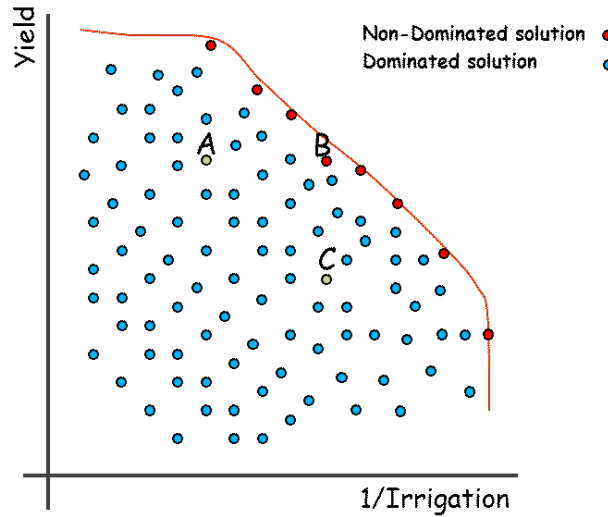


Fig 4.1: Example of efficient (red) and non-efficient (blue) strategies of irrigation and production

1.1.8 Efficiency and Dominance

Efficiency, which is the same idea as admissibility or noninferiority [Steuer 1989], is another primary concept in multi-objective optimization and is defined as follows:

A point, $x^* \in X$, is **efficient** if there does not exist another point, $x \in X$, such that $F(x) \leq F(x^*)$ with at least one $F_i(x) < F_i(x^*)$. Otherwise, x^* is inefficient.

The set of all efficient points is called the **efficient frontier**. Steuer also provides the following definition for nondominated and **dominated points**:

A vector of objective functions, $F(x^*) \in Z$, is **non-dominated** if there does not exist another vector, $F(x) \in Z$, such that $F(x) \leq F(x^*)$ with at least one $F_i(x) < F_i(x^*)$. Otherwise, $F(x^*)$ is dominated.

For all practical purposes, Definitions of efficient and non-dominated are the same. However, efficiency typically refers to a vector of design variables in the design space, whereas dominance refers to a vector of functions in the criterion space.

The definition of Pareto optimality is similar to that of efficiency, and a Pareto optimal point in the criterion space is often considered the same as a non-dominated point. However, efficiency and dominance were originally given more general, less common definitions in terms of domination structures and convex cones [Yu 1974], [Yu and Leitmann 1974]. Pareto optimality is a subtly distinguishable special case of efficiency, but this distinction is irrelevant in terms of practical applications.

1.1.9 Compromise Solutions

An alternative to the idea of Pareto optimality and efficiency, which yields a single solution point, is the idea of a compromise solution [Salukvadze 1971]. It entails minimizing the difference between the potential optimal point and a utopia point, also called an ideal point, which is defined as follows [Vincent and Grantham 1981]:

Utopia Point: A point, $F^0 \in Z^k$, is a utopia point iff for each $i = 1, 2, \dots, k$,

$$F_i^0 = \text{minimum}_x \{F_i(x) | x \in X\}.$$

In general, F^0 is unattainable. The next best thing is a solution that is as close as possible to the utopia point. Such a solution is called a compromise solution and is Pareto optimal. A difficulty with the idea of a compromise solution is the definition of the word close. The term close usually implies that one minimizes the Euclidean distance $N(x)$, which is defined as follows:

$$N(x) = |F(x) - F^0| = \left\{ \sum_i^k |F(x) - F_i^0|^2 \right\}^{1/2}$$

However, it is not necessary to restrict closeness to the case of a Euclidean norm [Vincent 1983]. In addition, if different objective functions have different units, the Euclidean norm or a norm of any degree becomes insufficient to represent closeness mathematically. Consequently, the objective functions should be transformed such that they are dimensionless.

CLASIFICACION OF MULTI OBJETIVE OPTIMIZATION METHOS

The variety of techniques for ‘solving’ an MCA problem has grown rapidly over recent decades. [Weistroffer et al. 2005]] review 79 MCA software packages which implement a variety of MCA methods. Recent review papers identify hundreds of MCA techniques for ranking or scoring options, weighting criteria and transforming criteria into commensurate units [Figueira et al., 2005]; [Pohekar and Ramachandran, 2004]; [Hayashi, 2000].

From a general point of view we must consider two types of approaches, depending on the type of problem to solve:

Multi-criteria Ranking and Benchmarking. Given a set of objects each described by multiple attributes or criteria (e.g., watershed characteristics, slopes, soils, land-cover, agricultural management practices, rainfall patterns) the system supports the interactive ranking of the set by any or all of the criteria in any arbitrary combination. The benchmarking concept introduces a context for evaluation, and relative positioning of objects in relation to known reference cases rather than isolated and in more difficult to interpret absolute terms in the absence of general standards that can be used as constraints.

Complex Optimization. In the previous case the set of alternatives were supposed to be given. If we have a model or set of models describing a complex system, we can generate any number of alternatives, and apply the above elements to identify a best, most desirable solution, and in fact design it automatically to meet all constraints and minimize or maximize the objective functions. Since large, complex system are usually non-differentiable unless simplified considerably, and all observation are highly uncertain, especially in the risk analysis domain, we extend the set of criteria and measure similarity in term of distance in a N dimensional behaviour space. The underlying methods is a hybrid of several heuristic methods, including Monte Carlo, stochastic hill-climbing, linear and dynamic programming, and evolutionary algorithms to make the search procedure more efficient and avoid computability issues of combinatorial explosion. However, for large systems, the method is very compute intensive, which is the price for a detailed and more realistic model description, coupled, dynamic, spatially distributed, non-linear.

Discrete MC Optimization. This is an implementation of the reference point methodology of multi-attribute theory. Its basic advantage is simplicity, the use of a minimum set of assumptions, so that it lends itself to interactive use. Here we use the N dimensional geometry of the behaviour space, defined by the set of alternatives, to define measures of achievement, the objective function, given the distance of any alternative from utopia, or a user-defined reference point. The implicit normalization of the criteria (dimensions) to the interval between nadir and utopia as a degree of (possible) achievement makes it possible to use an effective strategy without eliciting complicated weights or preferences from the user. The method first partitions the search space into dominated and nondominated alternatives (i.e., generating a Pareto-optimal sub-set) always depending on the user’s choice of the criteria to be considered, and any constraints specified.

1.1.10 Standard Classifications

Classification presented in Fig. 4.2 indicates generally adopted differentiation amongst approaches and mathematical mechanisms used to support evaluation of decision elements in search for optimal, compromise or best solution. Most important are:

- **MOLP** (Multiple Objective Linear Programming), a tool to select the best solution among the efficient ones. A number of different MOLP procedures have been reported, of which GP (Goal Programming) is best known. The weighted-sum technique and vector-maximum algorithms are regarded as members of the more frequently applied MOLP approaches. In agricultural/water management they are not frequently used.

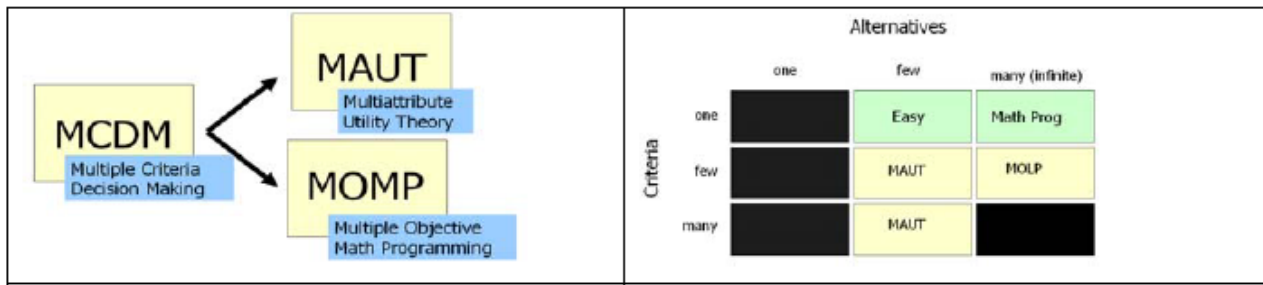


Fig 4.2: Multicriteria decision-making: classifications and characteristics

- **MOMP** (Multiple Objective Mathematical Programming) encapsulates several problem types, such as above mentioned MOLP, MOILP (Multiple Objective Integer Linear Programming), and NMOO (Nonlinear Multiple Objective Optimization). Among methods for solving multiple objective decision problems, a typical one is again GP. There is recently reported application of GP in India for selecting the best irrigation project including selection of best combination of 7 potential surface reservoirs to meet prescribed water demands, not only irrigational, [Raju and Pillai, 1999].
- **MAUT** (Multi-Attribute Utility Theory) gathers broad spectrum of methods to select the best solution among the nondominated ones, as illustrated in Fig. 4.1. Frequently used methods for solving MAUT problems are: (1) Analytic Hierarchy Process (AHP) [Saaty, 1980] characterised by pair wise comparisons among decision elements and linear additive utility function (also SMART - which stands for Simple Multiattribute Rating Technique; SMARTS – which is SMART with Swing weights; and SMARTER – to make things even simpler), and (2) Outranking methods (PROMETHEE and ELECTRE) characterised by producing a (weak) ordering of alternatives.

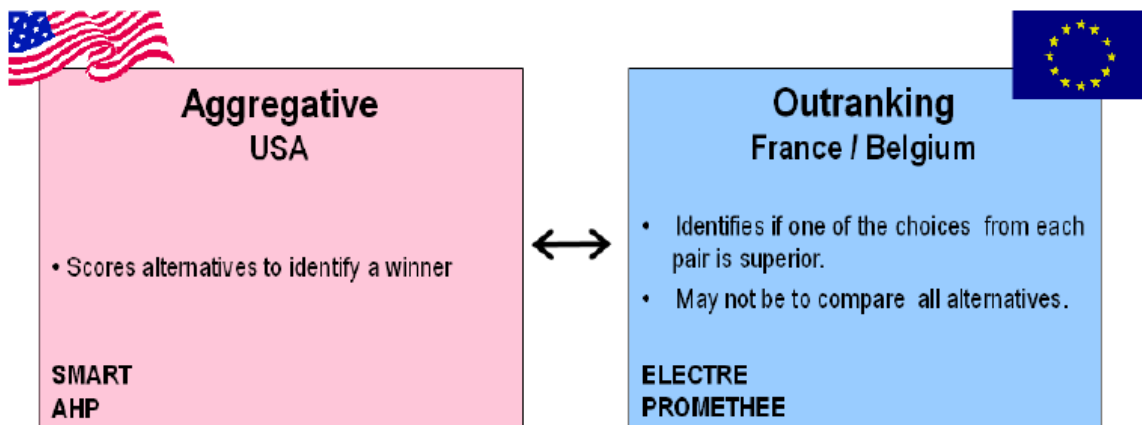


Fig 4.3: American and European school of thinking [Srdjevic et al. 2004]

1.1.11 Multicriteria Decision Making Methods

Two general multicriteria decision making (MCDM) approaches can be distinguished: the first referred to as ‘Top down design’ which is ‘objective led’, and the second one referred as ‘Bottom up design’ which is alternative led. They are also known as American and European school of thinking Fig. 4.3. Notice, however, that both ‘schools’ are present worldwide and that scientific community does not demonstrate any significant preference or bias among them.

In certain phase of the decision-making process the decision matrix (in different contexts also called product matrix, payoff matrix, performance matrix, decision table et.) is created. It is a prerequisite for most MCDM methods. Entries of this matrix represent scores (ratings) r_{ij} of alternatives (A_1, \dots, A_n) with respect to criteria (C_1, \dots, C_m).

Values (w_1, \dots, w_m) written above the matrix (1) are the importance weights of criteria defined by the DM, or derived in another way; they usually (but not necessarily) sum 1.

$$R = \begin{matrix} & \begin{matrix} (w_1 & w_2 & \dots & w_m) \\ C_1 & C_2 & \dots & C_m \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ r_{21} & r_{22} & \dots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{bmatrix} \end{matrix}$$

Several methods use matrix (1) directly such as:

•**SAW** (Simple Additive Weighting). This is one of the most simple, but nevertheless good decision making methods. Its results are usually very close to more sophisticated methods. SAW consists of three basic steps:

- 1 - scale the scores to make them comparable,
- 2 - apply criteria weights, and
- 3 - sum the values along rows and select best (top ranked) alternative.

•**SPW** (Simple Product Weighting). This method is similar to SAW, except the products of r_{ij} along rows of the matrix are used instead of summations. In SPW applications scaling is not necessary, as well as normalization, however both are permitted.

•**TOPSIS** (Technique for Order Preference by Similarity to Ideal Solution). It is rational and relatively simple method developed by [Hwang and Yoon, 1981]. The underlying concept is that most preferred alternative should not only have shortest distance from 'ideal' solution, but also longest distance from 'negative-ideal' solution. TOPSIS evaluates a decision matrix in several steps starting by normalizing columns and then multiplying values in columns by corresponding weights of criteria. Then, best and worst value in each column is identified followed by creation of two sets of these values across all columns named ideal solution and negative-ideal solution, respectively. In the next step so-called separation measures for all alternatives are computed based on their Euclidean distances from ideal and negative-ideal solutions (across all criteria). Finally, the relative closeness to ideal solution is calculated for each alternative, and alternatives are appropriately ranked. Top-ranked alternative is with the shortest distance from ideal solution and TOPSIS guarantees that it also has the longest distance from negative-ideal solution. In modified version of TOPSIS, which is also in use, the first step related to normalization is performed differently, achieving those entries in each column of normalized decision matrix sum 1. Also, ideal solutions are determined differently than in standard TOPSIS [Deng et al, 2000].

•**CP** (Compromise Programming). This technique ranks alternatives according to their closeness to so called 'utopia' point. The best alternative is the one whose point is at the least distance from utopia point in the set of efficient solutions. Minimisation of this closeness is a surrogate of the standard maximization of the criterion function. The distance measure used in CP is the family of L_p -metrics defined in especial way [Zeleny, 1982] and with a parameter p to implicitly express the DM's attitude to balance criteria ($p = 1$), to accept decreasing marginal utility ($p > 1$), or to search for absolutely dominant solution ($p \rightarrow \infty$). The most common value is $p = 2$. Whichever parameter value is used, an alternative with minimum L_p -metric is considered as the best.

Notice that above mentioned methods can be fuzzified [Triantaphyllou and Lin, 1996]. While standard versions are frequently used, there are not relevant reported applications of their fuzzy versions. Other important MCDM methods are:

•**AHP** (Analytic Hierarchy Process). This method has been developed in the 70ties and published in (Saaty, 1980). AHP decomposes a complex multi-factor problem into a hierarchy. It uses hierarchic structures, matrices and linear algebra to formalize the decision processes. The AHP determines the priorities of each alternative with the assigned weight for each alternative by analysing the judgmental matrices and by applying mathematical theory of eigenvalues and eigenvectors. AHP combines both subjective and objective judgments in an integrated framework based on ratio

scales from simple pair wise comparisons. In last 3 decades it has been used in for analysing various agricultural and water management problems see [Ramanathan and Ganesh, 1995]; [Srdjevic et al., 2002]; [Zoranovic and Srdjevic, 2003]; [Zhang et al., 2004]; [Chiou, 2004].

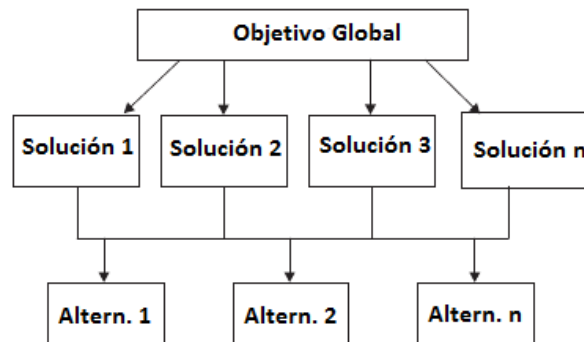


Fig 4.4: Example of the construction of the hierarchy of decision for the multicriteria analysis

•**PROMETHEE** and **ELECTRE**. These are two best known outranking methods developed by [Brans et al, 1986])and [Roy, 1968]. They are characterized by an aggregation of criteria, where multicriteria value is replaced by single criterion and complete dominance relation is established. Typically, in interactive versions of these methods the decision maker's preferences are not modelled globally, but incrementally. Enrichment of dominance relation is achieved by adding arcs to dominance relation and/or by building “fuzzy” dominance relations. Use of outranking relation is a decision aid itself; however it should be said that outranking methods in a way narrow the choices [Shafike et al, 1992]. Both methods are often used in the different fields of agricultural and water management. PROMETHEE, for example, is used for analysis and assessment of financial viability of agribusinesses [Baourakis et al, 2002], for simultaneous kinetic-spectrophotometric determination of carbamate pesticides [Ni et al, 2004] and for ranking of different agricultural production options (Parsons, 2002); ELECTRE is used for evaluation of floodplain restoration alternatives [Zsuffa and Bogardi, 1995]; combined with GIS in the model MEDUSAT for assessing the land suitability in Switzerland [Joerin et al, 1998]; and also for outranking a series of water pricing policies in the Ebro river basin of the Huesca region in Spain [Breuil et al., 2000].

•**DEA** (Data Envelopment Analysis). This is a special method that do not use decision matrix directly. While standard MCDM tools are used to select a best alternative, DEA evaluates the efficiency of a group of alternatives, but does not indicate a clear winner. DEA has a multicriteria flavour: minimize all inputs, and maximize all outputs. Standard version of DEA does not use DM's preferences over inputs and outputs, however, this can be done. There are several weight restrictions related to criteria that lead to various versions of the method [Sarkis, 2000]. An interesting application of this method in selecting best long-term water management scenario can be found in [Srdjevic et al, 2004].

1.1.12 Intelligent Support to the Decision-Making Process

The central issue in ranking management scenarios by technical system's performance is how to preserve objectivity of the process, i.e. to reduce or eliminate influence of the DM. Also we need to find the global optima in many real-life (environmental management) MOMP (Multi-objective mathematical programming) problems is a difficult task, especially when the search space has local extreme. Indeed, such problems often involve large and complex search spaces (non derivative), multiple conflicting objective functions, and a host of uncertainties that require consideration. In those situations, intelligent techniques could be the solution.

Amongst instruments, mechanisms, and methodologies that can be categorized as ‘intelligent’ support to the decision-making, three groups can be identified:

- Expert Systems (ES).
- Stochastic Search Engines (SSE) also called Evolutionary Algorithm (EA).

All they found place in engineering at various levels of implementation. While **ES** are self-contained and discipline-oriented, **SSE** are typically imbedded into more complex programming systems to serve as quick and efficient search mechanisms over infinite solution spaces, that is in solving multimodal and NP-hard optimization problems or in searching for undominated solutions within complex decision space. The EAs, such as genetic algorithms (GA), simulated annealing (SA), tabu search (TS), and multi-objective differential evolution (MODE) are natural candidates for solving these problems and are preferable to the MOMP methods because of their simplicity, flexibility, ease of operation, minimal requirements, and global perspective [Oduguwa et al., 2005]. The EAs operate on a population of potential solutions based on two principles: selection and variation. While selection mimics, the competition for reproduction and resources among living beings, variation imitates the natural capability of creating new living beings by means of recombination and mutation [Shen et al., 2010]. Multi-objective EAs have received tremendous attention in recent years [Ahn, 2006; Abraham et al., 2005].

•**ESs (Expert Systems):** ESs are considered as a special field of Artificial Intelligence. Their success lies in their ability to analyze large amounts of information according to pre-established rules resembling the reasoning of a human expert or group of experts. ES uses a collection of facts, rules of thumb, and other knowledge to help make inferences on how to deal with the problem under consideration. ESs differ substantially from conventional computer programs in that their goals may have no mathematical solution, and they must make inferences based on incomplete or uncertain information. Typical structure of advanced ES in environmental resources generally is: (1) a data base and interactive editor tools to maintain/compare multiple alternatives; (2) a multiple-layer (hierarchical) GIS covering the entire area as well as the areas immediately affected by individual projects (the GIS may use both vector data and satellite imagery); and (3) a set of special data bases, e.g. on plant coverage, meteorology, hydrography, water quality observations, population, forestry coverage, environmental technologies (such as waste water treatment), etc. Regarding architecture of ES, it includes:

- (1) Knowledge base with checklists, rules, background information and guidelines and instructions for the analyst;
- (2) Inference engine, that guides the analyst through a projects assessment in a simple menu-driven dialogue;
- (3) Report generator, that summarizes and evaluates the assessment or decisions.

•**SSE (Stochastic Search Engines):** The dominant classes of stochastic search engines are Simulated Annealing (SA), Tabu Search (TS), Genetic Algorithms (GAs) and Ant Colony Optimization (ACO). To understand the power of SSEs, recall that there are three main types of traditional (conventional) search methods:

- (1) Calculus-based.
- (2) Enumerative.
- (3) Random.

Calculus-based methods (also referred to as gradient methods), such as well-known conjugate-gradient or quasi-Newton method, use the information about the gradient of the function to guide the direction of search. If the derivative of the function cannot be computed, because it is discontinuous, for example, these methods often fail. Gradient-type methods are generally referred to as hill climbing. They do not adapt well to variable, fractal, or discontinuous surfaces, so they have serious shortcomings when applied to more complex, multimodal problems because of their inability to escape from local optima. Enumerative methods work within a finite search space: algorithm starts looking at objective function values at every point in the space, one at a time. Random search methods are strictly random walks through the search space while saving the best. For example GAs, as representative SSEs, differ from conventional optimization/search procedures in that:

- (1) they work with a coding of the parameter set, not the parameters themselves;
- (2) they search from a population of points in the problem domain, not a singular point;
- (3) they use payoff information as the objective function rather than derivatives of the problem or auxiliary knowledge;
- (4) they utilize probabilistic transition rules based on fitness rather than deterministic one.

On the other side, ACO emulates distant sharing of information that is usually considered as distributed intelligence.

Simulated Annealing (SA) is invented by [Kirkpatrick in 1983]. The SA is a generic probabilistic meta-heuristic model used to find the global optimisation in multicriteria problems with discrete search space, namely locating a good approximation to the global optimum of a given function in a large search space [Bertsimas and Tsitsiklis, 1993]. The name of the method and the inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects [Cerny, 1985]; [Kirkpatrick et al., 1983].

SA is applicable to problems for which little prior knowledge is available. It produces high-quality solutions for hard combinatorial optimization problems. Each step of the SA algorithm replaces the current solution by a random ‘nearby’ solution, chosen with a probability that depends both on the difference between the corresponding function values and also on a global parameter (called the temperature), that is gradually decreased during the process. The dependency is such that the current solution changes almost randomly when the temperature is high, but increasingly ‘downhill’ as the temperature moves towards zero. The allowance for ‘uphill’ moves saves the method from becoming stuck at local optima – which are the bane of greedier methods.

Tabu Search (TS) was proposed in its present form in 1989 by Fred Glover [Glover, 1989], although its roots are going back to the late 60’s and early 70’s. The TS is a meta-heuristic algorithm that belongs to the class of local search techniques and can be used to solve combinatorial optimisation problems. TS enhances the performance of a local search method by using memory structures. It is based on the premise that intelligent problem solving requires incorporation of adaptive memory. TS solves combinatorial optimization problems by guiding a hill-climbing heuristic to continue exploration without becoming confounded by a lack of improving moves, and without falling back into a local optimum from which it previously emerged. The admissible move is applied to the current solution in each iteration by transforming it into its neighbour with the smallest cost. Solutions that increase the cost function are permitted, and the reverse move is prohibited for some number of iterations in order to avoid cycling. The restrictions are based on a short-term memory function, which determines how long a tabu restriction will be enforced, or, alternatively, which moves are admissible in each iteration. In brief, TS is a meta-heuristic global technique that has to be adapted to the problem at hand for it to be efficient. TS has been applied successfully to a large number of hard optimization problems and has been shown to compare favourably with SA and GAs. The TS modifies the neighbourhood structure of each solution as the search progresses to explore regions of the search space that would be left unexplored by the local search procedure [Glover and Laguna, 1997].

Genetic Algorithms (GAs) derive their inspiration from the natural process of biological evolution [Goldberg, 1989]. Solutions are encoded into (often binary) strings or chromosomes and the GA operates on a population of these chromosomes. Significant difference between GA and the other global search techniques is that it allows for a parallel search of the space since a population of points is considered at each step instead of just a single point. A solution is represented as a “genome”. The optimization starts with an initial “population” of “genomes”. With each iterative step the “genomes” of the “population” are evaluated with a defined objective function and the “fittest genomes” are chosen to be recombined. The newly generated solutions or “offspring genomes” also are evaluated and the least “fittest genomes” are excluded from the population to maintain the original population size. Process iteratively evolves to the required solution by creation of new and new generations of chromosomes through operations of fitness-based selection and reproduction with crossover and mutation that are fundamentally similar to their natural analogy. A class of GAs comprises probably the most prominent and most popular intelligent algorithms nowadays.

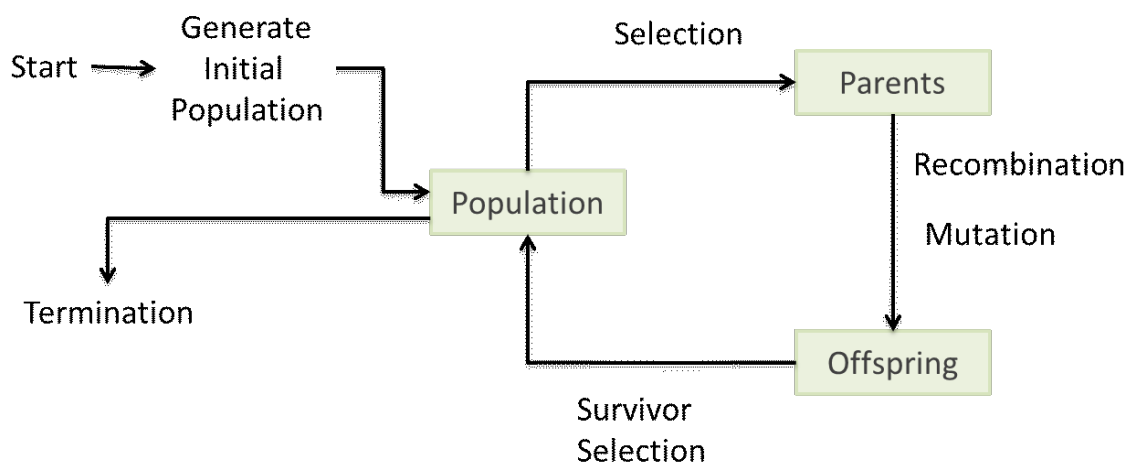


Fig 4.5: General Scheme of the Evolutionary Algorithm

While methods used in the scalarised problem generate a single (local) optimum, the evolutionary optimisation in MOO generates a representation of the complete Pareto optimal set. However, the visualization of the Pareto set is impractical for more than 2 (or at most 3) dimensions, thus, for simplicity we consider the local optima convergence.

Evolutionary algorithm optimizers are global optimization methods and scale well to higher dimensional problems. They are robust with respect to noisy evaluation functions, and the handling of evaluation functions which do not yield a sensible result in given period of time is straightforward. The algorithms can easily be adjusted to the problem at hand. Almost any aspect of the algorithm may be changed and customized.

In extending the ideas of single objective EAs, two challenges have to be addressed [Deb, 1999]:

- a) Finding solutions which lie in the Pareto optimal front
- b) Maintaining a diverse population to prevent premature convergence to a local optimum and achieve to a well distributed trade-off front.

In reality, the DM requires one solution irrespective of the many solutions that may be obtained in a MOO set up. Making the decision on a single solution out of many may prove to be a big challenge to the DM and would require provision of higher-level information which is often non-technical, qualitative and experience driven in nature. Ideally effort must be made to find a set of trade-off optimal solutions by considering all objectives to be important. After the trade-offs are found, then high-level qualitative information can be used to narrow down to one solution. This procedure is summarised in a two-step multiobjective optimisation as below:

- a) Step 1: Find multiple non-dominated points as close to the Pareto optimal front as possible with a wide trade-off among objectives.
- b) Step 2: Choose one of the obtained points using higher-level information.

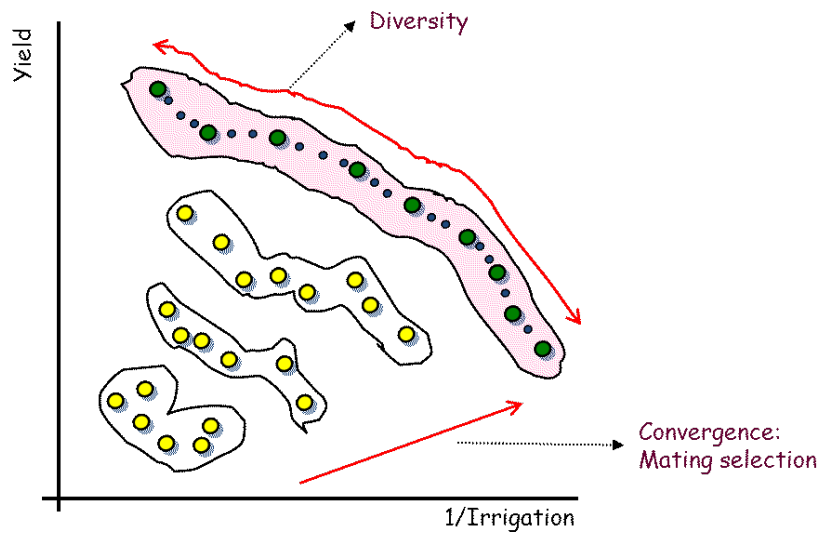


Fig 4.6: Example of EMO Convergence to the Pareto Optimal Front

Ant Colony Optimization (ACO): Insects' behaviour more and more serves as an inspiration for developing intelligent mechanisms to support decision-making processes in various areas of engineering. In answering the question what is it all about, it should be said that recent researches proved the ability of ants to find the shortest path to a food source, and when an obstacle blocks the most direct path, their ability to very quickly find the next best route. If its ability is translated to glitches on the Internet or distribution networks, then the ants can offer some solutions. For example, if the nodes on one Internet network are clogged with too much traffic, it's sometimes necessary to reroute new traffic. Ants that follow the shortest path are also those first making return trip to the food source. Therefore, their pheromone trail quickly becomes thicker. Even the heavier pheromone scents attract more ants and the shortest path is even further reinforced, there are always some ants that (meanwhile) follow their own trail and explore new routes. These individuals also lay down pheromone trails. So when, by analogy, a rock tumbles across the main route and traffic in the distribution network is jammed, the artificial ants are ready with a backup path.

This ant is assumed to be an agent, which moves from city to city on a TSP (refers to a ‘travelling salesman problem’) graph [Dorigo and Gambardella, 1997]. Therefore, if decision problem can be modelled as combinatorial problem, or precisely as TSP, than the use of ACO algorithm is straightforward. More and more applications of ACO can be found in pertinent literature for exploring large solution spaces.

METODOLOGY OF APPLYING MCA IN ENVIROMENTAL PROBLEMS

The wide variety of multi-criteria methods in use for water management required an upfront definition to guide our review. There are a variety of terms used to refer to MCA. Some other names include multiple objective decision support (MODS), multi-attribute decision making (MADM) and multi-criteria decision analysis (MCDA). These approaches share the same fundamental theoretical underpinnings and are collectively referred to in this paper as MCA. MCA can be defined as a decision model which contains:

- A set of decision options which need to be ranked or scored by the decision maker;
- A set of criteria, typically measured in different units; and
- A set of performance measures, which are the raw scores for each decision option against each criterion.

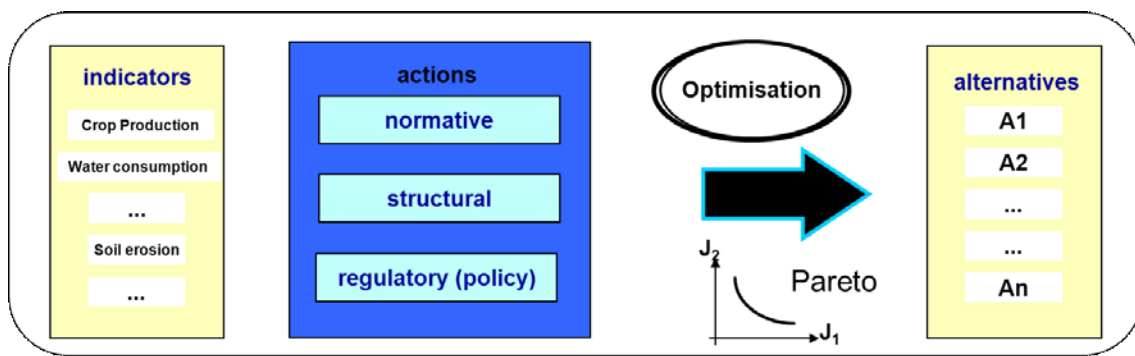


Fig 4.7: Generic outline of the designing alternatives process

The MCA model is represented by an evaluation matrix X of n decision options and m criteria. The raw performance score for decision option i with respect to criterion j is denoted by x_{ij} . A minimum requirement for the MCA model is at least two criteria and two decision options ($n \geq 2$ and $m \geq 2$). The importance of each criterion is usually given in a one dimensional weights vector W containing m weights, where w_j denotes the weight assigned to the j_{th} criterion. It is possible for X and W to contain a mix of qualitative (ordinal) and quantitative (cardinal) data.

A great variety of MCA algorithms can be used to either rank or score the decision options. The MCA algorithms will define, by some means, one or both of these functions:

$$r_i = f_1(X, W)$$

$$u_i = f_2(X, W)$$

Here r_i is an ordinal number representing the rank position of decision option i and u_i is the overall performance score of option i . The solution of r_i and u_i occurs within a broader MCA decision making process. Numerous authors [RAC, 1992], [Howard, 1991] have described the MCA process and it generally contains the following stages:

1. **Choose decision options.** Usually there is a finite set of decision options which are to be ranked or scored, which creates a ‘discrete’ choice problem. In some cases the aim is to identify an optimum quantity subject to constraints, which creates a ‘continuous’ choice problem.
2. **Choose evaluation criteria.** The criteria are used to measure the performance of decision options. They should be non-redundant and relevant to the decision maker’s objectives [Keeney and Raiffa 1993]. Redundant criteria are typically highly correlated and measure the same underlying factor.
3. **Obtain performance measures** (x_{ij}) for the evaluation matrix. The values for x_{ij} may be either ordinal or cardinal, and can be sourced from expert judgements or other environmental and economic models.

4. **Transform into commensurate units.** An MCA problem will almost always contain criteria in different units. Transformation places them onto a commensurate scale, often 0 to 1, so they can be meaningfully combined in the overall utility function.
5. **Weight the criteria.** Criteria are rarely of equal importance to the decision maker and a variety of methods are available to assign weights at either cardinal or ordinal levels of measurement.
6. **Rank or score the options.** At this stage the weights are combined with the performance measures to attain an overall performance rank or score for each decision option. A wide range of ranking algorithms, which use ordinal and/or cardinal properties of the performance measures, can be used in this task.
7. **Perform sensitivity analysis.** Systematic variation of the weights, performance measures and ranking algorithms can reveal where the MCA model needs strengthening and the robustness of results given input assumptions.
8. **Make a decision.** The MCA model aims to inform, but not make, the final decision. There is typically a requirement for some level of human judgement to account for relevant issues that could not be adequately modelled in the MCA.

This process often involves several iterations, with earlier stages being revisited as the analysis unfolds.

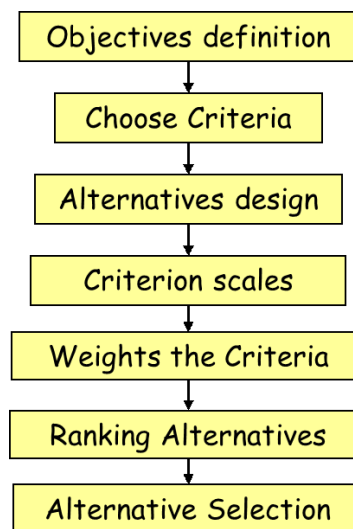


Fig 4.8: Generic outline of the multicriteria decision methodologies

Improving decision making for human and natural resource management requires consideration of a multitude of non-economic objectives, such as biodiversity, ecological integrity, and recreation potential. Furthermore, the values of environmental attributes, such as biodiversity, cannot be properly measured using monetary criteria; appropriate non-monetary criteria need to be developed.

The MCDA process (fig 1) typically defines objectives, chooses the criteria to measure the objectives, specifies alternatives, transforms the criterion scales into commensurable units, assigns weights to the criteria that reflect their relative importance, selects and applies a mathematical algorithm for ranking alternatives, and chooses an alternative [Howard, 1991], [Keeney, 1992], [Hajkowicz and Prato 1998]. Many authors have described and reviewed MCDA techniques (e.g., [Herath, 1982], [Smith and Theberge, 1987], [Stewart, 1992], [Hayashi, 2000]).

DECISION SUPORT SYSTEM

A DSS is computer based, including hardware, software, and data; it must assist in making non-trivial decisions, but beyond that, there is little agreement. Analysing the literature, the overwhelming number of cases that claim DSS status refer to relatively simple information and model systems that focus on problem representation and in most cases, WHAT-IF type scenario analysis.

A considerably smaller group addresses optimization tools with usually a strong Operations Research and mathematical programming focus.

The basic functions of a DSS include:

- (1) Identify and structure the problem, and define a consistent preference structure in terms of criteria, objectives, and constraints.
- (2) Design alternatives that provide solutions to the problem as posed.
- (3) Select preferred solutions from the set of alternatives based on the preference structure.

Computerized models underpin resource management and provide for the encapsulation and transfer of knowledge about the agricultural processes. To be useful to managers, they are commonly augmented by other tools, which allow for scenario description, data exploration, explanation and assessment [Fedra, 1993]. Traditionally this has been achieved by developing Decision Support Systems (DSSs), which contain and enhance a suite of models, and are tailored to the clients' needs and expertise.

The development of user-friendly software and operating systems, and increased access to and familiarity with computers among decision makers are probably the main reasons for such a growth in both research and practice. Recent applications in western countries demonstrated that certain DSSs, which incorporate simulation and optimization models with interactive graphics capabilities [Labadie, 1995]; [Azevedo et al, 2000]; [LABSID, 2004], were helpful in encouraging the acceptance of these techniques in practice.

Many experts in early 90-ties have stressed the need for better communication between analysts and decision makers in substantial improving the usefulness of models. A good example of advances made in recent years is existence of advanced interactive user-friendly computer systems such as Web-HIPRE [Decisionarium, 2004] for decision-making through Internet. However, it is evident that there still exists a gap between theory and practice even in the West, and that decision makers have to articulate better their information needs while modellers must communicate effectively their results and co-operate with decision makers. The complexity and long development time, inherent in building DSS, are the most important reasons that prevented their wider use in developed and particularly undeveloped countries, including those in Balkan region. There is an obvious lack of case studies in which the performance of agricultural/water related DSSs has been evaluated in the appropriate institutional settings.

The decision tools and DSS could be best described in terms of their general type and by focusing on the stage in the decision process being supported, from information gathering through storage to exploring alternatives. Several issues are worthily to discuss below:

1.1.13 Information Collection and Management.

Decision-making requires information that needs to be collected. An important source of social data is the governmental census. Other governmental and non-governmental sources could be opinion polls, natural resources inventories and commercial registers. These data need to be extracted and transferred from their current databases to the decision maker's database. Existing data are supplemented by surveys focused on the needs of the decision problem at hand. Different computer aids can be used, and most recently the use of the Internet may help if appropriate communication infrastructure is established. Another important source of information is remote sensing from satellites; this data would typically feed into geographic information systems (GIS). Large amounts of raw data from different sources and in different formats must be verified and often converted into formats suitable for other components of a DSS. This exemplifies the well-known problem of interoperability and data interchange. It should be also noted that data integrity is critical for computer-based modelling and knowledge based systems. A computerized statistical methods and rule-based systems are provided for analysis and pre-processing of data to check the integrity by discovering of discrepancies in received information.

1.1.14 Modelling and Rational Decision Support.

To explore the consequences of particular courses of action, models and facilities should build. That will enable manipulation and experimentation with variables representing characteristics of real systems within a predefined time scale. The most common modelling tools are simulation-modelling techniques. A complex DSS requires a collection of models. The software architecture should include facilities for model repository, selection of appropriate models and composition of subsets of models to solve complex problems. Therefore, the DSS should behave as open structure. Computers using mature software packages commonly support methods used in rational decision-making, such as multicriteria analysis and linear programming. The uncertainty prevalent in decision problems related to development, cause necessity for handling uncertainty and risk in these packages. This area of decision support is strongly problem-oriented and is in continuous development.

1.1.15 Visualization and the Human Interface.

People participating in the decision-making process prefer to have pictures and diagrams to help them visualize the situation about which they must make a decision. Of more recent origin is the ability to display the rich and complex maps in multiple colours with a fine level of detail. These maps can display the spatial relationships between the elements of interest, and the geographical distribution of those elements through theme maps under user control. Humans have very powerful spatial reasoning capabilities, and the display of geographic data can tap into that reasoning power.

1.1.16 Group Decision Making.

Sometimes decision-making is a group process through which various stakeholders need to reach agreement. Tools for group working and workflow are important in the common situation when the stakeholders involved are geographically dispersed and communication networks need to be exploited. Systems are commercially available using "groupware" to support collaborative working, the holding of meetings and so on. The recent rapid growth of the Internet enables making this support widely useful.

1.1.17 Knowledge Capture and Representation.

To capture knowledge about particular decision problem, one possible way is to do it through Knowledge Based Systems (KBSs) and Expert Systems (ESs). KBS generally contains a knowledge base and a problem solving mechanism known as inference method. ES is sometimes used as a synonym for KBS. Capturing the rules of KBS/ES can itself require great expertise, and a good technology here is that of rule induction - the system 'learns' the decision rules from examples of correct decision. Another learning method is imbedded in neural networks and technologies for their training. Collaboration between several KBS/ES could be useful in solving some problems in a way similar to decision making by an interdisciplinary group of experts. The application of KBS to capture expertise in sustainable development falls into two main categories: where the KBS is the core of the DSS, and where the KBS is an auxiliary to some other system. The first category is where there is human expertise in a subject area. The second category is where there is a need for expertise in handling the results from a certain model and/or software package in order to let the results of that system be comprehensible to the decision makers.

1.1.18 DSS Integration.

A key capability of DSS is the interoperation of tools obtained from different sources. Decision maker would be able to choose the appropriate tool for a particular job and provide for input and output of transfer information as he explores the alternative decisions. This transfer of information is still difficult at present, in spite of rapid development in the field. There is a clear move towards more open systems that will provide for data interchange in producing and monitoring natural resources such as plant coverage, water, or forests. Standards developed for GIS in United States, United Kingdom, France, Canada and Australia are good example in this regard. As a toolbox, a GIS allows performing spatial analysis using its geoprocessing or cartographic modelling functions such as data retrieval, topological map overlay and network analysis. Of all the geoprocessing functions, map overlay is probably the most useful tool for planning and decision-making. For example, there is a long tradition of using map overlays in land suitability analysis. Decision makers can also extract data from the database of GIS and input it into different modelling and analysis programs together with data from other database or specially conducted surveys. GIS has been widely used in information retrieval, development control, mapping, site selection, land use planning, land suitability analysis, and programming and monitoring. GIS can be seen as one form of spatial DSS.

REVIEW OF BIOPHYSICAL MODELS LINKED TO MCO

Nowadays, the MCDA method is widely used in many water resources and environmental management problems where conflict management and stakeholders' participation is of prime importance. This method is a very useful tool for practical analysis to facilitate learning process between analyst and stakeholders [Marttunen and Suomalainen, 2005]. Various studies have been undertaken on the theory and practical applications of MCDA [Marttunen and Suomalainen, 2005]; [Belton and Stewart, 2002]; [Hobbs and Meier, 2000]. Some good applications on water resources and environmental management have been done by [Gregory and Keeney, 1994], [Hostmann et al., 2005], [Raju et al., 2000], [Herath, 2004], [Lahdelma et al., 2000], [Marttunen and Hämäläinen, 1995], [Brown, 1984], [Ridgley and Rijsberman, 1992], [Stewart and Scott, 1995], [Arvai and Gregory, 2003], [Bella et al., 1996], [Ganoulis, 2003], [Ning and Chang, 2002] etc. Stakeholders' involvement is one of the crucial parts of the MCDA applications. Some of the ways of arranging stakeholders' participation reported in previous studies are interviews with individual stakeholders or small groups, public consultations, workshops and decision conferences etc. [Hostmann et al., 2005]. Another important task in the MCDA applications is the evaluation of alternatives. Most of the methods are based on multiple objective programming and generating alternatives by maximizing a set of objectives [Rajabi et al., 2001]; [Ko et al., 1994]. There are some models that iteratively generate alternatives from stakeholders' preferences [Cai et al., 2004].

Water resource management decisions are typically guided by multiple objectives measured in a range of financial and non-financial units [Gough and Ward, 1996]. Often the outcomes are highly intangible and may include items such as biodiversity, recreation, scenery and human health. These characteristics of water planning decisions make multiple criteria analysis (MCA) an attractive approach. MCA can be defined as a grouping of techniques for evaluating decision options against multiple criteria measured in different units [RAC, 1992]; [Voogd, 1983]. A decision option is an action, or project, which contributes to the decision maker's objectives. In discrete choice MCA there are a finite set of decision options being appraised. Weights can be assigned to criteria to represent their relative importance. Many researchers have found that MCA provides an effective tool for water management by adding structure, auditability, transparency and rigour to decisions [Dunning et al., 2000]; [Joubert et al., 2003]; [Flug et al., 2000]; [Nayak and Panda, 2001].

In connection with climate change this might intensify existing impacts on the environment and lead to new conflicts between ecosystem services [Schröter et al. 2005, IPCC 2007]. For example, increased water use for irrigation could conflict with water demands for domestic or industrial uses, and lead to negative ecological implications [Bates et al. 2008]. Also, soil loss through erosion may increase due to climate change, an effect which could be aggravated through changes in land management [Lee et al. 1999]. To prevent continued degradation of natural resources, policy will need to support farmers' adaptation while considering the multifunctional role of agriculture [Olesen and Bindi 2002]. Hence, effective measures to minimize productivity losses and preserve finite natural resources need to be developed at all decision levels, and scientists need to assist decision makers in this process [Salinger et al. 1999].

Multi-objective optimization methods in connection with biophysical models have shown great potential for addressing such issues of opposing management goals [Ines et al. 2006, Bryan and Crossman 2008, Higgins et al. 2008, Sadeghi et al. 2009, Meyer et al. 2009, Whittaker et al. 2009 and Latinopoulos 2009]. Bryan and Crossman [2008] developed an optimization-based regional planning approach to identify geographic priorities for onground natural resource management actions that most cost-effectively meet multiple natural resource management objectives. Higgins et al. [2008] applied a multi-objective integer programming model, with objective functions representing biodiversity, water runoff and carbon sequestration. Sadeghi et al. [2009] applied an optimization approach to maximize profits from land use, while minimizing erosion risk. [Udias et al., 2007] and [Meyer et al., 2009] coupled SWAT (Soil and Water Assessment Tool) with an optimization routine to determine optimum farming system patterns to reduce nitrogen leaching while maintaining income. Similarly, Whittaker et al. [2009] applied SWAT in connection with a Pareto-optimization approach considering profits from land use and chemical pollution from farm production. [Latinopoulos, 2009] applied optimization to a problem of water and land resource allocation in irrigated agriculture with respect to a series of socio-economic and environmental objectives. Such approaches can be very useful to support the development of regional land use adaptation strategies. However, they have not been used yet in combination with scenarios of climate change.

Several authors also have combined the use of biophysical and multiobjective programming models. [Fernandez-Santos et al., 1993] addressed the nitrate pollution problem in the province of Cordoba, in Spain, using the NTRM crop simulation model and a multi-objective programming model at the farm level. Flichman [Flichman et al., 1995 a, b] used the EPIC biophysical model to generate information on yields and nitrate pollution and a multi-objective bicriterion model, in order to analyze the impacts of the Common Agricultural Policy Reform on nitrate pollution in several European regions. More recently, Teague et al. used a bicriterion stochastic farm model combined with the

EPIC-PST simulation model. The mathematical model employed the Target MOTAD technique, testing for the stochasticity of the environmental outcomes while maximizing net return. The two environmental criteria considered were nitrate and pesticide pollution.

[Pandey and Hardaker, 1995] gave an overview of bio-economic modelling as a useful tool for studying the interaction between farm management practices and economic criteria to analyze sustainability of farming systems.

Water resource planning and management is a sub-field of natural resource management in which decisions are particularly amenable to MCA [Romero and Rehman, 1987]. Decisions in water management are characterised by multiple objectives and multiple stakeholder groups. Outcome measures are in multiple financial and non-financial units. Decision makers are increasingly looking beyond conventional benefit cost analysis towards techniques of MCA that can handle a multi-objective decision environment [Prato, 1999]; [Joubert et al., 1997]; [Bana e Costa et al., 2004].

Effectiveness of this integration methodology is, however, directly influenced by the capability of the biophysical model used to estimate the real effect for a given environmental (water or land) use and management alternative and its ability to account for the various environmental factors that may affect the processes. Fortunately, over the last three decades, advances in hydrological science and engineering, as well as computer capabilities, have stimulated the development of a wide variety of mathematical simulation models for such estimates. The most comprehensive simulation techniques are process-based (physically based), distributed models such as SHE [Abbott et al., 1986], AGNPS [Young et al., 1987], ANSWERS-2000 [Bouraoui & Dillaha, 1996] and Soil and Water Assessment Tool, or SWAT [Arnold et al., 1999].

These models have replaced traditional lumped, empirical models that relate management and environmental factors to runoff and sediment yield through statistical relations. Distributed models are able to capture the spatial and temporal heterogeneity of environmental factors such as soil, land use, topography and climate variables. Hydrological models themselves, however, are useful only for evaluating what-if scenarios and testing potential management alternatives. They are unable directly to solve water resources management and control problems that require the explanation of a range of available alternatives.

A comprehensive decision-making framework for watershed management requires the integration of a hydrological simulation model and a suitable multi criteria optimization technique that is capable of solving complex control problems. These integrative methods, has been increasingly popular in water resources related fields and has provided solutions for large-scale problems in areas of reservoir management [Yeh, 1985]; [Unver & Mays, 1990]; [Nicklow & Mays, 2000], bioremediation design and groundwater management [Wanakule et al., 1986]; [Yeh, 1992]; [Minsker & Shoemaker, 1998)] design and operation of water distribution systems [Cunha & Sousa, 2000]; [Sakarya & Mays, 2000]; [Udías et al., 2012] and watershed management, [Muleta & Nicklow, 2001]; [Nicklow & Muleta, 2001]; [Udías et al., 2011]. [Nicklow, 2000] provides a comprehensive review of the benefits of these kinds of approach, which include a reduced need for additional simplifying assumptions about the problem physics in order to reach an optimal policy and a decrease in size of the overall optimization problem

TYPES OF MCA APPLICATION

In this study eight types of MCA application in water resource management were identified:

1. *Catchment management.* This involves applications of MCA to problems of whole catchment management, which are often concerned with land use and land management patterns. An example of this application can be drawn from [Chang et al., 1997] where MCA methods are employed to evaluate land management strategies within a catchment in Tweng–Wen reservoir watershed in Taiwan. Land use within the catchment is guided by economic and environmental objectives.
2. *Ground water management.* These studies use MCA specifically for the management of groundwater, often to determine the best ways of remediation of contaminated groundwater supplies. It is illustrated by [Almasri and Kaluarachchi, 2005] who use MCA to evaluate options for managing nitrate contamination of groundwater in the Sumas–Blaine aquifer in Washington State, US.
3. *Infrastructure selection.* These studies are concerned with choosing major water infrastructure supply options for a city or region. Most involve urban water supply. An example comes from [Eder et al., 1997] who use MCA techniques to evaluate 12 water supply infrastructure options for the Austrian part of the Danube River. The options involve major infrastructure such as hydroelectric power schemes.
4. *Project appraisal.* These studies use MCA to rank or score a set of water management projects which often involve some form of water condition restoration activity. For example, [Al-Rashdan et al., 1999] use MCA to prioritise a set of projects aimed to improve the environmental quality of the Jordan River.

5. *Water allocation.* These applications involve decisions about how much of a limited water resource is allocated to competing uses. An example comes from [Agrell et al., 1998] who use MCA to inform water release decisions from the Shellmouth Reservoir in south-west Manitoba, Canada. Water release aims to deliver on multiple social, economic and environmental uses.
6. *Water policy and supply planning.* This involves the evaluation of policy options (e.g., levies, legislation, awareness raising) and longer term strategic planning for a region's water supply. An example comes from [Joubert et al., 2003] where MCA is used to evaluate water demand and supply management policies in Cape Town, South Africa.
7. *Water quality management.* These papers involved an application of MCA primarily involving the evaluation of options aimed specifically at improving water quality (as opposed to supply). They often involve human and ecosystem health objectives. An example comes from [Lee and Chang, 2005] where MCA is used to develop a water quality management plan for the Tou–Chen River Basin in northern Taiwan.
8. *Marine protected area management.* This involves the use of MCA to manage nearshore marine environments. One such study by [Fernandes et al., 1999] uses MCA to evaluate coral reef management options in the Caribbean.

An additional category was termed 'method papers.' These papers explored MCA methods for water management on a theoretical level. Some papers involved elements of two or more categories.

The majority of applications are in water policy evaluation, water supply planning and infrastructure selection. These decisions often have deep and long-lasting impacts on numerous stakeholders. They involve a requirement to handle multiple objectives for which MCA is potentially well suited. Relatively few applications have occurred in marine protected area management [Fernandes et al., 1999]. These decisions typically involve multiple objectives and applications within this field may grow.

REASONS FOR USING MCA IN WATER MANAGEMENT

The water management MCA studies reviewed in this report provide insights to why MCA is adopted. This section briefly explores some of the main reasons researchers adopted MCA over alternative decision making frameworks.

In many studies MCA was found to provide transparency and accountability to decision procedures which may otherwise have unclear motives and rationale [Brown et al., 2001]; [Joubert et al., 1997]. Transparency in MCA is achieved by explicitly stating and weighting decision criteria. The reasons for choice are made explicit and past decisions can easily be audited. For example, [Dunning et al., 2000] argue that MCA's 'logical' and 'well documented' approach makes it suitable to support decisions under Section 316(b) of the US Clean Water Act, which deals with the selection of remediation technologies for mitigating point source water pollution.

It is interesting to consider that whilst transparency is typically seen as a strength of MCA it may be a deterrent for some. Sometimes decision makers, either overtly or covertly, do not want to be too transparent. [Dunning et al., 2000] suggest MCA may not be adopted for US water quality legislation because it is too 'explicit'.

Conflict resolution is a common reason for adopting MCA. It becomes an issue when multiple perspectives are applied to a single water management decision [Cai et al., 2004]; [Yin et al., 1999]; [Chuntian and Chau, 2002]; [Mustajoki et al., 2004]. A striking example comes from Mimi and [Sawalhi's, 2003] use of multi-criteria techniques to inform the allocation of Jordan River water amongst Palestine, Israel, Syria, Lebanon and Jordan.

The ability of MCA to help in conflict resolution partly results from its transparency. All parties are required to explicitly state their preferences through a structured process. It is then possible to identify areas of agreement and disagreement, thereby managing conflict. MCA can be used to identify shared solution space from multiple perspectives [Cai et al., 2004].

Multi-stakeholder engagement and community participation were also seen as reasons for adopting MCA in water management decisions [Greiner et al., 2005]; [Fernandes et al., 1999]; [Nayak and Panda, 2001]. [Brown et al., 2001] used MCA to engage stakeholders and build consensus based approaches to the management of a marine protected area. They found that (p432):

The inclusion of stakeholder views and values within a rigorous framework can, potentially, provide rich information for regulators seeking to manage marine park resources in partnership with other stakeholders." ... "We believe that participatory approaches are complementary, not oppositional, to decision support tools such as MCA."

Another common reason for adopting MCA for water management is that MCA uses formal axioms of decision theory to inform choice. This helps ensure the analysis is logical and robust. [Schultz, 2001] argues that basing the US Environmental Protection Agency's Index of Watershed Indicators (IWI) on multiattribute utility theory would improve internal consistency and rigour. The adoption of formal rules for decision making can assist with auditability. An auditor can use an MCA model to recreate the decision problem at the time choices were made. Auditability is another reason for adopting an MCA approach.

[Joubert et al., 1997] and [Prato, 1999] argue for the adoption of MCA to supplement benefit cost analysis (BCA). The two main limitations of BCA identified by these authors are: (a) a requirement for all outcomes to be expressed in monetary units and; (b) difficulties with achieving a fair distribution of resources amongst stakeholders. Water management decisions typically have important non-financial factors (e.g., health, biodiversity) and multiple stakeholder interests. The MCA framework ensures a robust analysis whilst permitting non-financial and distributional issues to be incorporated. This is prompting analysts to explore and apply MCA. However, [Joubert et al., 1997] note that MCA and BCA are complementary methods each with different roles in decision analysis. It is not a question of 'Which one is best?' but rather 'Which tool is best suited to a particular problem?'

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ANNEX 1: OTHER CLASIFICATION OF MDCA METHODS

1 OTHER CLASIFICATION OF MDCA METHODS

A general classification of MCDA methods is the one suggested by Belton and Stewart (2002) because it reflects more directly the range of their application. They classify MCDA methods into three broad categories:

- **Value measurement models:** “numerical scores are constructed in order to represent the degree to which one decision option may be preferred to another. Such scores are developed initially for each individual criterion, and are then synthesized in order to effect aggregation into higher level preference models”;
- **Goal, aspiration or reference level models:** “desirable or satisfactory levels of achievement are established for each criterion. The process then seeks to discover options which are closest to achieving these desirable goals or aspirations”;
- **Outranking models:** “alternative courses of action are compared pairwise, initially in terms of each criterion in order to identify the extent to which a preference for one over the other can be asserted. In aggregating such preference information across all relevant criteria, the model seeks to establish the strength of evidence favouring selection of one alternative over another”.

In the first group, the values of alternatives reflect a preference order. These preferences are required to be consistent with a relatively strong set of axioms. Though in practice value measurement is not applied in such a rigid framework, these axioms: (a) “impose some form of discipline in the building up of preference models”; (b) “help the decision-makers to obtain greater understanding of their own values and to justify their final decisions when required”; (c) “encourage explicit statements of acceptable tradeoffs between criteria”.

The second group presents methods for “situations in which decision makers may find it very difficult to express tradeoffs or importance weights, but may nevertheless be able to describe outcome scenarios, expressed in terms of satisfying aspirations or goals for each criterion”. Available courses of action (alternatives) are systematically eliminated until, in the view of the decision maker, a satisfactory level of performance for this criterion has been ensured. The process should be seen in a dynamic perspective. The decision maker should be able to backtrack the elimination process and cycle through it.

The outranking models focus “on pairwise evaluation of alternatives, identifying incomparability’s as well as assessing preferences and indifferences”. Preferences evolve “as part of the MCDA process within the context of the choices to be made”.

	S. 1	S. 2	S. 3	S. n
S. 1	1	3	2	5
S. 2	1/3	1	1/2	1/2
S. 3	1/2	2	1	2
S. 4	1/5	2	1/2	1

Fig A.1: example of peer comparison between objectives

MCDA techniques encompass a wide variety of methods which belong to different axiomatic groups and schools of thought. Keeney (1982) defines MCDA as a formalization of a common sense approach to decision problems that is appropriate when decision problems are too complex to be solved by informal use of common sense. Several distinct schools of thought appear in the MCDA literature. Value and utility based approaches assume that there is a value function or utility function. Multiple attribute value theory (MAVT), multiple attribute utility theory (MAUT), and the simple multi-attribute rating technique (SMART) are the most common approaches within this school. MAVT belongs to the quantitative riskless category and MAUT and ELECTRE belong to the quantitative risk category. The Analytic Hierarchy Process (AHP), developed by Saaty (1977, 1980), uses the same paradigm as MAVT, and is the source of several other variants, such as the geometric mean approach and various modifications to incorporate risk and multi-valued outcomes [Duke and Aull-Hyde 2002].

The most widespread ways or classify the multi-objective optimization methods are based on the:

- Depending on the alternatives domain

- Depending on the moment in which decision makers introduce his preferences.

ALTERNATIVES DOMAIN CLASSIFICATION

The MCDM methods are frequently used to solve real world problems with multiple, conflicting, and incommensurate criteria. MCDM problems are generally categorised as **continuous or discrete**, depending on the domain of alternatives. Hwang and Yoon (1981) have classified the MCDM methods into two categories: **multi-objective decision-making** (MODM) and **multi-attribute decision-making** (MADM). The main distinction between the two groups of methods is based on the number of alternatives under evaluation. MADM methods are designed for selecting discrete alternatives while MODM are more adequate to deal with multi-objective planning problems, when a theoretically infinite number of continuous alternatives are defined by a set of constraints on a vector of decision variables [Korhonen et al., 1992; Hayashi, 2000; Belton and Stewart, 2002].

MODM has been widely studied by means of mathematical programming methods with well-formulated theoretical frameworks. MODM methods have decision variable values that are determined in a continuous or integer domain with either an infinitive or a large number of alternative choices, the best of which should satisfy the DM constraints and preference priorities (Hwang and Masud, 1979; Ehrgott and Wiecek, 2005). MADM methods, on the other hand, have been used to solve problems with discrete decision spaces and a predetermined or a limited number of alternative choices. The MADM solution process requires inter and intra-attribute comparisons and involves implicit or explicit tradeoffs (Hwang and Yoon, 1981). Figure 1 shows the MCDM classification used in this paragraph. A more thorough distinction between these two groups of methods was made by Malczewski (1999) based on the differences pointed by Hwang and Yoon (1981) and Zeleny (1982).

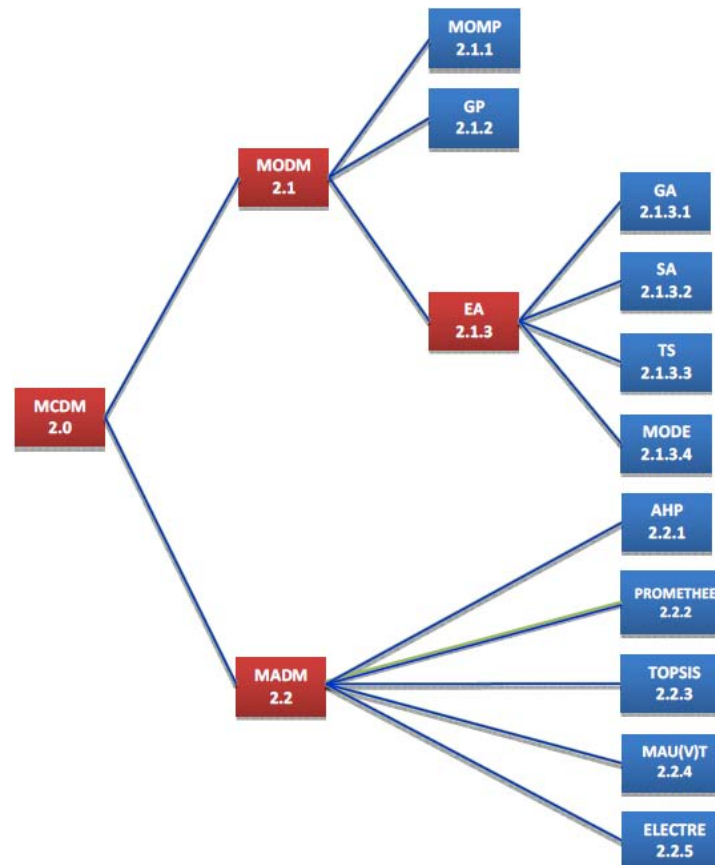


Fig A.2: MCDM Classification based on Domain

1.1.1 Multi-objective decision-making

Most real-life decision problems involve multiple and conflicting objectives, sometimes subject to certain constraints. MODM is commonly used to solve these problems characterised by multiple and conflicting objective functions such as maximizing performance while minimising fuel consumption of a vehicle simultaneously over a feasible set of decisions. An MODM model considers a vector of decision variables, objective functions, and constraints (Chankong and Haimes, 1983; Ehrgott and Wiecek, 2005; Hwang and Masud, 1979; Kahraman and Kaya,

2008). The goal is to optimise the objective functions, while the DMs choose a solution among a set of efficient solutions since MODM problems rarely have a unique solution (Zhang et al., 2007).

One of the most challenging problems in MODM applications is related to the identification or approximation of a family of points known as the Pareto-optimal set (Ehrgott, 2005). Pareto optimality is a measure of efficiency in multi-objective optimisation. A large number of methods have been proposed to generate the Pareto optimal set in the literature. These methods vary from simple approaches, requiring very little information, to the methods based on mathematical programming techniques, requiring extensive information on each objective and the preferences of the DMs. There is no 'one size fits all' methodology for MODM problems. A method that works well in theory can fail in practice, one that works well on some problems may not be suitable for others. The majority of MODM methods fall into two broad categories: those employing mathematical programming techniques and those using evolutionary algorithms (EA).

1.1.2 Multi-objective mathematical programming (MOMP)

The central issue in MOMP is the direct involvement of the DM in the process of searching for the best compromise solution on the basis of the individual preferences. A number of MOMP models and categories have been proposed since the early 70s. In MOMP, a set of linear functions are optimised subject to a series of linear constraints. When at least one objective function or constraint function is non-linear, we get a multi-objective non-linear programming problem. The MOMP becomes a convex problem, when all the objective functions and the constraint set are convex and non-convex optimisation problem, when at least one objective function or the constraint set is non-convex (Chinchuluun and Pardalos, 2007).

The methods for solving MOMP problems are also classified as a priori methods, interactive methods, and a posteriori methods (Hwang and Masud, 1979). In a priori methods, the DM expresses his/her preferences before the solution process (e.g., setting goals or weights for the objective functions). In interactive methods, the dialogue phase with the DM is interchanged with the calculation phase and the process usually converges after a few iterations to the most preferred solution. In a posteriori methods, the efficient solutions (all of them or a sufficient number of them) are generated before the DM intervenes and selects the most preferred solution.

MOMENT DECISION MAKERS INTRODUCE PREFERENCES CLASSIFICATION

When the decision-maker articulates his or her preference on the different objectives, never, before, during or after the actual optimization procedure

When solving the MOO problem, we also seek to investigate the existence of a Pareto optimal solution. Since by deriving Pareto optimal solutions we only obtain a partial order of solutions, we require information on preference from the DM so as to be able to select the most preferred solution in the Pareto set. For this, there are two methods that are discussed:

1. **Non-Interactive methods:** This is where the DM is not available to give preference or he gives preference a priori or a posteriori. A priori methods are described in the non-interactive approach methods where the DM specifies his preferences before the analyst generates the Pareto optimal solution set while in the a posteriori methods, the DM makes his preferences known from an already generated Pareto optimal solutions set.
 - a. **No-preference methods** There is no opinion incorporated by the DM as it is possible that he does not feature in the solution process. The MOO is solved by finding a compromise solution say a solution in the middle of the Pareto optimal set.
 - b. **A Priori Methods** In this method, the DM's role only occurs before the generation of the Pareto optimal solutions where he clearly stipulates his preferences initially. Several approaches that will be reviewed in this method are also applicable in a posteriori methods. Lexicographic, weighting, goal programming
2. **Interactive Methods:** Here the DM is fully involved in the solution process and gives his input on preference. This arguably the best method for achieving the most preferred solution. In this methodology, participation and input of the DM is required throughout an iterative process between the decision making phase and the optimisation phase. After every iteration, the DM verifies that the output meets his preferences which have already been stipulated

Below in this section, we make a short review of the different approaches to scalarising the general MOO problem to a single objective optimisation problem. Alternatively, we can solve MOO directly without scalarising the problem. These techniques are described in the next section of this report (MOO Algorithms Reviews)

The neoclassical economic approach based on maximization of a single objective (i.e., utility for consumers and profit for businesses) has limited applicability in multi-attribute decision problems in natural resource management (Joubert et al. 1997).

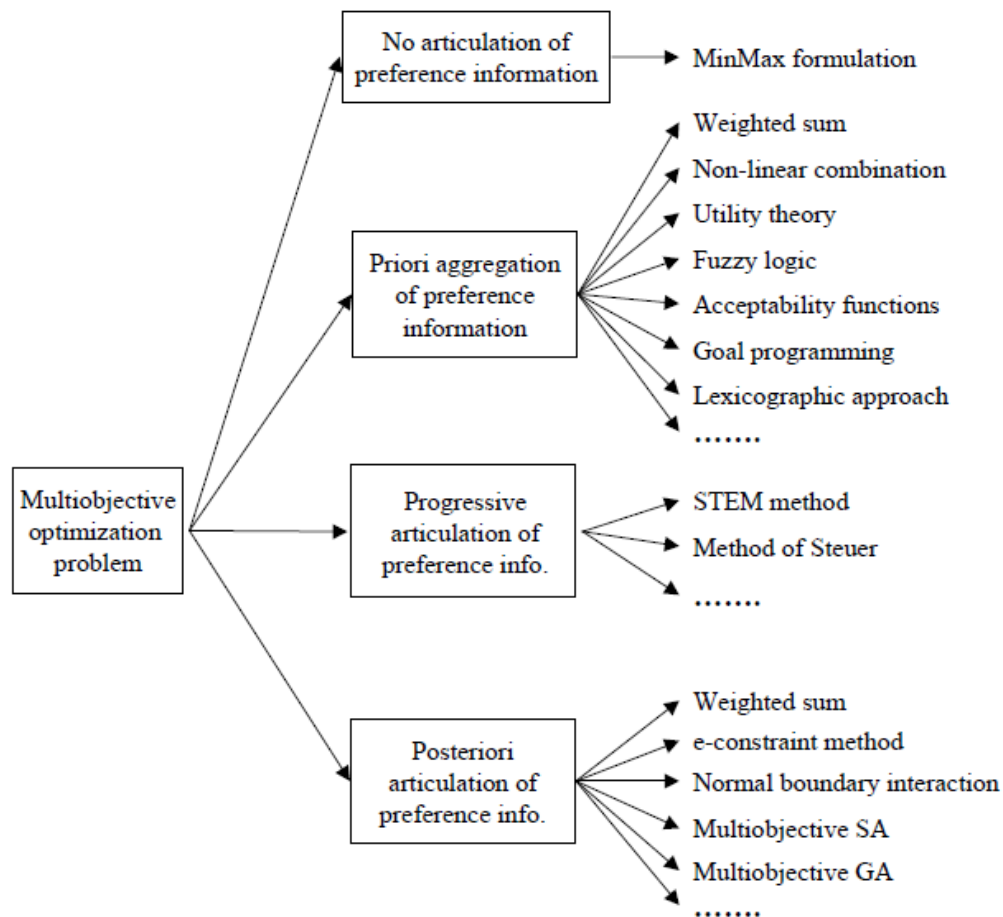


Figure A.3: A classification of some methods for multiobjective optimization

GOAL PROGRAMIN (GP)

The GP, which was first suggested by Charnes et al. (1955) and Charnes and Cooper (1961), is an analytical method devised to tackle decision-making problems where goals are assigned to multiple, possibly conflicting attributes, and where the DM seeks a satisfactory and sufficient solution by minimising the non-achievement of the corresponding goals. There are several classes of GP depending on the nature of the goal functions, decision variables, and coefficients. For example, goal functions may be linear or non-linear; decision variables may be continuous, discrete, or mixed; and coefficients may be deterministic, stochastic, or fuzzy. Surveys of GP are available in the works by Schniederjans (1995), and Zanakis and Gupta (1985).

LEXICOGRAPHIC APPROACHES

In lexicographic approaches, the decision-maker determines an order in which the objectives have to be optimized. Like in a dictionary where A precedes B, the decisionmaker determines that objective i precede objective j. This implies that solutions are ordered by first evaluating them based on the foremost objective. If a set of solutions have comparable values in the foremost objective, the comparison continues on lower level objectives until the solutions can be distinguished. The disadvantage with lexicographic approaches is that not all objectives might be considered. Lexicographic methods are not so commonly used by them self in engineering design, but jointly with other techniques, such as in goal programming or as a part of a selection mechanism in genetic algorithms.

SCALARIZED SINGLE OBJECTIVE OPTIMISATION PROBLEMS

In previous section (Preference in Pareto Optimal Solutions) of this report, we have reviewed the different approaches to scalarising the general MOO problem to a single objective optimisation problem. Scalarisation rewrites the problem in a form that can easily be solved with the algorithms used in solving a single objective optimization problems. In addition to that, the newly rewritten form also incorporates the input of the decision makers (DM).

Solving this kind of problem results in obtaining one Pareto optimal solution that is preferred by the DM in a single run. Alternatively, we can solve MOO directly without scalarising the problem. For this, we use advanced algorithms that solve the MOO and simultaneously give a set of Pareto optimal solutions in a single run. Now, we briefly review algorithms that can be used on the scalarised problems and the evolutionary optimisation methods.

1. Numerical Optimisation Methods in Scalarized Single Objective Optimisation Problems:

The methods to be applied are dependent on whether the problem is linear, non-linear, continuous or discrete or some combination. Linear programming has been successfully applied in determination of optimisation operation policies for water supply systems. Quadratic programming has been applied when pumping costs depend on the drawdown. Fixed costs of installing new wells in ground water planning strategies use discrete optimization algorithms such as dynamic programming, branch and bound, local search and evolutionary algorithms. Monitoring of network design and groundwater remediation give rise to combinatorial problems that may also be solved using a discretized optimisation algorithm.

Problems in water engineering are mostly non-convex and solving them with the methods discussed above in this section can often be a daunting task. A recent trend of mimicking biological processes in optimisation called bio-inspired optimisation methods has emerged. These methods mimic the different biological processes in biology and translate them to algorithms in optimisation.

The advantages for these methods include: they require very little knowledge on the problems being solved, they are robust and support parallel computing. Some of the bio-inspired methods include: evolutionary algorithms that mimic evolutionary theory, ant colony optimisation methods that mimic the movement of ants and particle swarm optimisation which mimic movement of birds/fish in a swarm.

FUZZY LOGIC APPROACHES

The concept of fuzzy sets is based on a multi-valued logic where a statement could be simultaneously partly true and partly false. In fuzzy logic, a membership function μ expresses the degree of truthfulness of a statement, in the range from $\mu=0$, indicating that the statement is false to $\mu=1$ for truth. This is in opposite to binary logic where a statement can be only false or true.

In an optimization problem the membership function enables us to associate a normalized value to each objective $\mu_i(f_i(x))$, which expresses the degree of satisfaction of the considered objective i . The value of $f_i(x)$ is fuzzified by μ to yield a value in the rang $\{0,1\}$, which quantifies how well a solution satisfies the requirements. Examples of two membership functions are depicted in next figure.

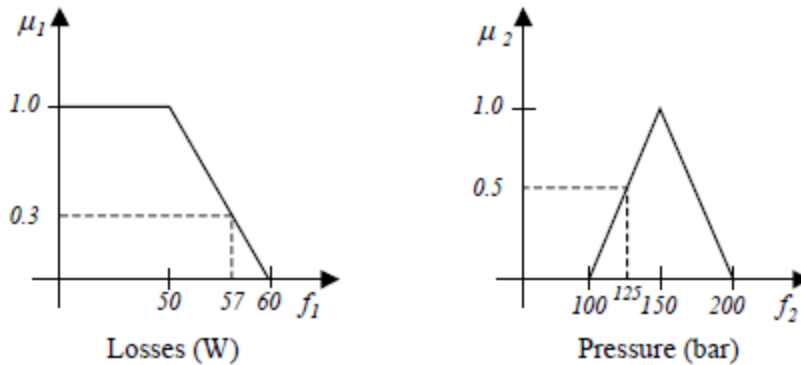


Figure A.4: A classification of some methods for multiobjective optimization

In Figure A.4 we consider a fluid power system design, where we want to keep the losses low, say 50W is acceptable whereas 60W is not. We also want to have a constant system pressure of 150 bar. The corresponding

membership functions could then look like in Figure 7. A membership function can have any shape. However, in the literatura piecewise linear functions are the most common.

Ones the fuzzification has been performed the actual value of each objectives have been transformed into logical values. These values have to be aggregated to one in order to get an overall value for the design. In binary logic this is accomplished by the AND operator. However, in fuzzy logic the AND operator could be implemented by several different rules. The most common ones are the min operator and the product operator. The min operator returns as an output the minimum value of the mi on which is operates. As in binary logic, if one mi equals zero the output is zero. The product operator returns the product of all individual operators. This formulation is also compatible with the one of binary logic. The overall objective function could consequently be expressed as:

$$F_{fuzzy}(\mathbf{x}) = \min(\mu_1(f_1(\mathbf{x})), \mu_2(f_2(\mathbf{x})), \dots, \mu_k(f_k(\mathbf{x}))) \text{ or}$$

$$F_{fuzzy}(\mathbf{x}) = \prod_{i=1}^k \mu_i(f_i(\mathbf{x}))$$

The overall fuzzy optimization problem is formulated according to equation

$$\begin{aligned} \max \quad & F_{fuzzy}(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in S \end{aligned}$$

MULTI-ATTRIBUTE DECISION-MAKING

MADM methods are used for circumstances that necessitate the consideration of different options that cannot be measured in a single dimension. Each method provides a different approach for selecting the best among several pre-selected alternatives (Janic and Reggiani, 2002). The MADM methods help DMs learn about the issues they face, the value systems of their own and other parties, and the organisational values and objectives that will consequently guide them in identifying a preferred course of action. The primary goal in MADM is to provide a set of attribute-aggregation methodologies for considering the preferences and judgements of DMs (Doumpos and Zopounidis, 2002). Roy (1990) argues that solving MADM problems is not searching for an optimal solution, but rather helping DMs master the complex judgements and data involved in their problems and advance towards an acceptable solution. Multi-attributes analysis is not an off-the-shelf recipe that can be applied to every problem and situation. The development of MADM models has often been dictated by real-life problems. Therefore, it is not surprising that methods have appeared in a rather diffuse way, without any clear general methodology or basic theory (Vincke, 1992). The selection of a MADM framework or method should be done carefully according to the nature of the problem, types of choices, measurement scales, dependency among the attributes, type of uncertainty, expectations of the DMs, and quantity and quality of the available data and judgements (Vincke, 1992). Finding the 'best' MADM framework is an elusive goal that may never be reached (Triantaphyllou, 2000).

ANALYTICAL HIERARCHY PROCESS (AHP)

AHP is a MADM approach that simplifies complex and ill-structured problems by arranging the decision attributes and alternatives in a hierarchical structure with the help of a series of pairwise comparisons. AHP can be a powerful tool for comparing alternative evaluation systems and design concepts in CE. Dyer and Forman (1992) describe the advantages of AHP in a group setting as follows:

1. the discussion focuses on both tangibles and intangibles, individual and shared values
2. the discussion can be focused on objectives rather than alternatives
3. the discussion can be structured so that every attribute can be considered in turn
4. the discussion continues until all relevant information has been considered and a consensus choice of the decision alternative is achieved.

Saaty (2000) argues that a DM naturally finds it easier to compare two things than to compare all things together in a list. AHP also examines the consistency of the DMs and allows for the revision of their responses. AHP has been applied to many diverse decisions because of the intuitive nature of the process and its power in resolving the complexity in a judgemental problem. A comprehensive list of the major applications of AHP, along with a description of the method and its axioms, can be found in Saaty (1994, 2000), Weiss and Rao (1987), and Zahedi (1986). AHP has proven to be a popular technique for determining weights in multi-attribute problems (Shim, 1989;

Zahedi, 1986). The importance of AHP and the use of pairwise comparisons in decision-making are best illustrated in the more than 1,000 references cited in Saaty (2000).

The main advantage of AHP is its ability to rank alternatives in the order of their effectiveness in meeting conflicting objectives. AHP calculations are not complex, and if the judgements made about the relative importance of the attributes have been made in good faith, then AHP calculations lead inexorably to the logical consequence of those judgements. AHP has been a controversial technique in the operations research community. Harker and Vargas (1990) show that AHP does have an axiomatic foundation, the cardinal measurement of preferences is fully represented by the eigenvector method, and the principles of hierarchical composition and rank reversal are valid. On the other hand, Dyer (1990a, 1990b) has questioned the theoretical basis underlying AHP and argues that it can lead to preference reversals based on the alternative set being analysed. In response, Saaty (1990) contends that rank reversal is a positive feature, when new reference points are introduced.

PREFERENCE RANKING ORGANISATION METHOD FOR ENRICHMENT EVALUATION (PROMETHEE)

The PROMETHEE family of outranking methods was first introduced by Brans (1982) in the form of partial ranking of alternatives (PROMETHEE I). Subsequently, the method was extended by Brans and Vincke (1985) to a full ranking approach, which is presently known as PROMETHEE II. A few years later, several versions of the PROMETHEE methods such as PROMETHEE III, IV, V, and VI were developed to help with more complicated decision-making situations (Brans and Mareschal, 2005). The PROMETHEE methods have been successfully applied to various fields, including environment management (Martin et al., 2003; Queiruga et al., 2008), hydrology and water management (Pudenz et al., 2002; Hermans et al., 2007), and energy management (Goletsis et al., 2003; Madlener et al., 2007).

Among the family of PROMETHEE method, PROMETHEE II is fundamental to the implementation of the other PROMETHEE methods (Behzadian et al., 2010). The central principle of PROMETHEE II is based on the pairwise comparison of alternatives along each attribute that is to be maximised or minimised. The implementation of PROMETHEE II requires relevant information concerning the weights and preference function of the attributes. For each attribute, the preference function translates the difference between the evaluations obtained by two alternatives into a preference degree ranging from 0 to 1. In order to facilitate the selection of a specific preference function, Brans and Vincke (1985) proposed six basic types, namely: usual attribute, U-shape attribute, V-shape attribute, level attribute, V-shape with indifference attribute, and Gaussian attribute. These six types are particularly easy to define.

PROMETHEE takes into account the amplitude of the deviations between the evaluations of the alternatives within each attribute, eliminates the scaling effects completely, reduces the number of incomparabilities, provides information on the conflicting nature of the attributes, and offers sensitivity tools to test easily different sets of weights (Brans and Mareschal, 2005). Gilliams et al. (2005) have shown that PROMETHEE II is slightly preferable to both ELECTRE III and AHP, based on user friendliness, simplicity of the model strategy, variation of the solution, and implementation. Al-Shemmeri et al. (1997) have shown that PROMETHEE is easier than ELECTRE III to understand by the DMs and simpler to manage by the analysts. Despite its distinct advantages, the great weaknesses of PROMETHEE are its structuring of the decision problem and determination of the weights (Macharis et al., 2004).

MULTI ATTRIBUTE UTILITY (VALUE) THEORY [MAU(V)]

The MAUT, developed by Keeney and Raiffa (1993), is a systematic method for identifying and analysing multiple variables to provide a common basis for arriving at a decision. The key element in MAUT is to derive a multi-attribute utility function for which single utility functions and their weighting factors are necessary. Since its development, various applications of the MAUT have been reported in many real decision-making problems such as the selection of an energy resource (Abouelnaga et al., 2009), risk ranking of natural gas pipelines (Brito and deAlmeida, 2009), evaluation of public risk preferences in forest land-use choices (Ananda and Herath, 2005), and selection of the best scenario for the radioactive substances exposed to the environment (Hwang, 2004).

Utility independence is a central concept in MAUT. Various utility-independence conditions imply specific forms of utility functions; however, only additive and multiplicative forms are generally used in practice. MAUT enables the DM to incorporate preference and value trade-offs for each metric and measure the relative importance of each attribute (Keeney and Raiffa, 1993). It is easy to understand and explain to DMs and provides a more practical methodology due to an easier computational analysis (Collins et al., 2006). The judgements in MAUT are made explicitly. Its value information can be used in many ways to help clarify a decision process, and DMs, typically learn a great deal through these joint efforts to construct their views on their preferences. However, the determination of the maximum and minimum ranges of the attributes and deriving work of the utility functions require a lot of time and effort in the MAUT (Kim and Song, 2009).

ELIMINATION AND CHOICE TRANSLATING REALITY (ELECTRE)

The ELECTRE method is a family of outranking methods developed by Roy (1973) to rank a set of alternatives. Soon after the introduction of the first version known as ELECTRE I, this approach has evolved into a number of variants. Today, the most widely used versions are known as ELECTRE II and ELECTRE III (Wang and Triantaphyllou, 2008). ELECTRE is a procedure that sequentially reduces the number of alternatives the DM is faced with in a set of non-dominated alternatives. The ELECTRE method is especially well-known in Europe. It has been extensively applied in many real application cases, including environment management (Rogers and Bruen, 1998; Hobbs and Meier, 2000), education system (Giannoulis and Ishizaka, 2009), water resources planning (Anand, 1995), and waste management (Hokkanen and Salminen, 1997).

The ELECTRE approach has a long history of successful practical applications in various problem domains (Achillas et al., 2010). With the ELECTRE, the DM is able to take into account either quantitative or qualitative attributes (Achillas et al., 2010). ELECTRE is quick, operates with simple logic, and has the strength of being able to detect the presence of incomparability; it uses a systematic computational procedure, an advantage of which is an absence of strong axiomatic assumptions (Shanian and Savadogo, 2006). While the applications of ELECTRE are well-documented in the literature, many authors have identified the allocation of weights as a major shortcoming of the method (Rogers and Bruen, 1998). In ELECTRE, similar to PROMETHEE, differences in attribute values are not taken into account totally; it does not matter how much an attribute value is better than that of another attribute (Salminen et al., 1998).

POSTERIORI ARTICULATION OF PREFERENCE INFORMATION

There are a number of techniques which enables to first search the solution space for a set of Pareto optimal solutions and present them to the decision-maker. The big advantages with these type of methods is that the solution is independent of the DM's preferences.

The analysis has only to be performed once, as the Pareto set would not change as long as the problem description are unchanged. However, some of these methods suffer from a large computational burden. Another disadvantage might be that the DM has too many solutions to choose from. There is however methods that supports in screening the Pareto set in order to cluster optimal solutions.